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COMPETITION BETWEEN TRADITIONAL AND LOW-COST AIRLINES FOR LOCAL HUB TRAFFIC

BY: JAMES M. NISSENBERG

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Abstract

It is conventional wisdom among informed observers of the U.S. airline industry that the passengers who fly full-service, hub-and-spoke-style, "traditional" airlines like American, United and Delta are significantly different from those who fly so-called "low-cost" airlines Southwest, RenoAir and Valujet. The former supposedly value level-of-service attributes like frequent flights, frequent flyer program, pre-assigned seating and first class cabin, while the latter are mostly concerned with obtaining a low fare. In markets where traditional and low-cost airlines compete, one would expect that the number of passengers flying each airline has statistically different responses to changes in important airline transport supply and market socioeconomic variables. However, few studies have tried to quantify these differences.

This thesis tests the idea that traditional and low-cost airline passengers belong to different market segments. A series of econometric demand models are developed separately for the traditional and low-cost airline for short-haul markets in which the two compete. The markets connect the traditional airline's hub airport with some of its "spoke" cities. Elasticities of demand are calculated for population, per capita income, average fare, nonstop frequency, flight time, cross-fare and cross-frequency. To determine if traditional and low-cost airline passenger elasticities also differ by level of competition, demand models are estimated for three separate hub airports.

Estimated demand model elasticities strongly suggest that traditional and low-cost airline passengers have significantly different valuations of airline trip attributes. The values of exogenous market variables also appear to have a differential effect. Specifically, changes in average fare and flight time seem to have a stronger effect on the number of low-cost airline passengers, while changes in population and per capita income seem to have a stronger effect on the number of traditional airline passengers. Flight frequency seems to have an effect sensitive to the relative number of individual airline flights, but independent of carrier type. Cross-fare and cross-frequency elasticity estimates indicate that, in general, passengers perceive traditional and low-cost airlines as rather poor substitutes.

Thesis Supervisor: Dr. Peter P. Belobaba
Title: Associate Professor of Aeronautics and Astronautics

Dedicated to my Grandfather Samuel Nissenberg and the Memory of My Grandparents
Rose and Milton Grey and Sara Grace Nissenberg.

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Finally, I'd like to give a shot right out to my sister Ashley in California. She's all that, know what I'm saying?

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1. Introduction

1.1 Thesis Setting and Objective

A popular theory of airline competition is that the passengers who fly large, full-service, hub-and-spoke-style "traditional" airlines like American, United and Delta are by and large not the passengers who fly smaller, no-frills, "low-cost" airlines like Southwest, RenoAir and Valujet. Traditional airline passengers are generally perceived as more sensitive to airline service characteristics like flight frequency, in-flight and on-ground service and frequent-flyer programs, while low-cost airline passengers are thought to be mainly interested in price. Although it is almost certainly true that there will be some mix of these passenger types on competing traditional and low-cost airline flights, that mix will almost certainly be weighted towards service-sensitive business travelers on the traditional airline flight and price-sensitive leisure travelers on the low-cost airline flight.

As any airline manager will say, the monetary benefit to more precisely defining the characteristics of the passengers an airline carries is not trivial. Airlines need to know what types of passengers they carry because this information helps them to plan everything from the number of seats they should allocate to different passenger types to competitive market strategy. It is this latter use for passenger data that it is important when a traditional airline and a low-cost airline compete against each other for passengers in one or more origin-and-destination (O&D) markets. Here, the advantage to having greater knowledge about the types of passengers one carries relative to one's competitor can be a significant advantage in pricing, scheduling, marketing new products and even new market entry. For example, if the traditional airline knows that raising its fares will cause few of its passengers to fly the low-cost airline, then it will raise its fares and make more money than it otherwise would have.

If it is true that passengers on traditional and low-cost airline flights do not value different attributes of the airline product -- like price, schedule and on-board service -- as equally important, then the existence and magnitude of these differential valuations ought to be empirically testable. Although one way to do this would be to use surveys, for example, such qualitative methods have the disadvantages that passengers often remember their priorities differently than when they made their flight selection, and that only the most interested (or bored) passengers reveal significant amounts of information about themselves.

A better way to derive traditional and low-cost airline passenger characteristics would be to use quantitative techniques like those found in classic econometric analysis. The advantage of econometrics is not only that it gives actual numerical answers to what effect changes in airline product offerings will have on passenger numbers, but that it uses actual passenger data, revealing choices that passengers have already made. If econometric equations could be derived relating traditional or low-cost airline passenger demand to, say, changes in important socioeconomic and transport supply variables that affect passenger choice of airline, then each airline would have valuable information about the effects of changes in market variables relative to its competitor.

The objective of this thesis is to estimate econometric models for traditional and low-cost airline passenger demand in common O&D markets. Specifically, equations will be developed to estimate the effects of the most basic socioeconomic -- population and per capita income -- and own-airline and cross-airline transport supply variables -- population, per capita income, average fare, nonstop frequency, flight time, cross-fare and cross-frequency on traditional and low-cost airline passenger demand. Moreover, these equations will be estimated for the traditional and low-cost airline at three separate traditional hub airports where the traditional airline faces different levels of low-cost airline competition for traffic in local hub markets (markets in which passenger origin and destination correspond to the hub city and cities linked to the hub through nonstop flights).

Hopefully, model estimation will provide evidence of three different phenomena. First, different socioeconomic and transport supply variables will have differential effects on the number of traditional versus low-cost airline passengers in every competitive scenario. Second, these effects will differ according to the level of traditional and low-cost airline competition at the traditional airline hub. Last, although traditional and low-cost airline elasticities will differ according to their competition level, these differences will occur mainly within rather than between the traditional and low-cost airline. In other words, individual traditional and low-cost airline explanatory variable elasticities will be generally higher (or lower) than those for the other airline independent of the actual competitive scenario.

1.2 Thesis Structure

The remainder of this thesis is divided into six chapters. Chapter 2 defines the terms "traditional" and "low-cost" as applied to different U.S. airlines, and describes some general characteristics of traditional and low-cost airlines. Specifically, differences in route network, marketing and service, and cost structure are discussed. These are the main areas in which traditional and low-cost airline company structure differs and a key to understanding the reasons for the various competitive strategies that each airline type pursues.

Chapter 3 introduces the setting and framework under which traditional and low-cost airline demand models will be developed and estimated later in the thesis. First, the local hub market is defined and illustrated with a real-world example. Then, major local hub market airline choice variables such as airfare, flight frequency, airline preference and the role of yield management systems are described. Last, to provide background for the differential airline elasticities expected to be estimated later in the thesis, the relative importance that one would expect traditional and low-cost airline local hub market passengers to place on the airline choice variables is explained.

Chapter 4 provides an overview of the use of econometric modeling in estimating air travel demand relationships and introduces the local hub market competitive scenarios estimated in this thesis. The chapter begins by reviewing and critiquing the air travel demand modeling literature, explaining why certain explanatory variables are basic determinants of airline demand and justifying a multiplicative functional form for the airline demand model. Next, the modeling procedures specific to the traditional and low-cost airline demand functions estimated in this thesis are described. Third, the summary statistics that will be used to compare elasticity estimates are reported. The chapter ends with insight into the *a priori* differential elasticity estimates one would expect from model estimation.

Chapter 5 presents results and interpretation for traditional airline, low-cost airline and total market demand model estimation at the three traditional airline hub airports in Phoenix, Salt Lake City and Atlanta. For each competitive scenario, background and descriptive statistics are given for each airline to provide a sense of the level of inter-airline competition and the range of explanatory variable values used in the data set. Next, demand model summary statistics are reported with comments. Finally, individual airline elasticity estimates are summarized, and the reasons for elasticity differentials exhaustively interpreted with reference to the descriptive statistics and the discussion of basic local market airline choice variables in Chapter 3.

Chapter 6 extends the discussion of individual competitive scenario differential elasticity estimates to a comparison across all competitive scenarios. For each explanatory variable used in the demand models, elasticity ranges are grouped by airline and competitive scenario, and the general "rule" that seems to apply for the elasticity differential stated. This rule is explained with reference to the elasticity estimates and the Chapter 3 discussion on the determinants of local market airline choice.

Finally, Chapter 7 reviews the objectives in estimating separate traditional and low-cost airline demand models, the process used to develop these models, and the main research findings. Although the demand models estimated in this thesis provide some general indications of the differential traditional/low-cost airline effects of changes in basic socioeconomic and transport supply variables, better specified and/or customized airline demand models are necessary before these results can be applied to actual airline decision making. To this end, several directions for further research are provided with illustrative examples.

2. Comparing Traditional and Low-Cost Airlines

2.1 Definitions of Traditional and Low-Cost

It is hard to find any two observers of the U.S. airline industry able to agree on a nomenclature by which to separate large, hub-and-spoke-style carriers like American, United and Delta from smaller, lower-cost low-fare carriers of differing route structures like Southwest, Valujet and RenoAir. Although there are many terms to divide carriers by history (traditional, post-deregulation, new entrant), unit cost (high-cost, low-cost), fare differential (high fare, low fare), route structure (hub-and-spoke, point-to-point, mixed) or corporate size (major, national, regional), there are few that separate based on the critical difference between these two sets of airlines: operating philosophy. The terms that have been offered, like full-service or no-frills, are unsatisfying because (1) airlines like Southwest and RenoAir offer some services, like frequent-flier mileage, that would be expected only on full-service airlines and (2) competition is blurring the level of service distinction between airlines as full-service carriers cut costs by cutting meals and on-board service quality.

Although there is no simple way to express the whole of an airline's strategy in one word or phrase, two terms whose connotative definitions have come to symbolize the philosophical split between airlines like American, United and Delta, as opposed to Southwest, Valujet and Reno Air are "traditional" and "low-cost". Historically, the word traditional has denoted carriers founded before deregulation in the late 1970s. However, in practice, it has come to mean the largest, hub-and-spoke-style, full-service airlines regardless of when they began scheduled service. Note that this definition of traditional corrects the main shortcomings of the literal definition, namely that America West Airlines (whose operations date back only to 1983) is now included in the group of "traditional" carriers and Southwest Airlines (which began service in 1971) is now excluded.

Low-cost used to simply mean an airline with low costs per available seat-mile (ASM).[1] However, America West, whose operational strategy clearly places it among the traditional carriers, has about the lowest unit costs in the airline industry. Now it seems that airlines must meet three criteria to be considered low-cost. First, they must have unit costs below about $.08/seat-mile. Second, their on-ground and in-flight service must be frugal and standardized for all passengers. Last, they must be price leaders in the markets in which they operate. In other words, low-cost airlines are also low-fare airlines.

In this thesis, the terms traditional and low-cost will be used according to the connotations just developed. "Traditional" will refer to the largest, hub-and-spoke, full-service airlines, a list that includes United, American, Delta, Northwest, USAir, Continental, TWA and America West.[2] "Low-cost" will refer to low unit-cost, low-frills, low-fare airlines like Southwest, Valujet, RenoAir, Western Pacific, Vanguard, and Air South. Although no longer operating, Morris Air (bought by Southwest in 1994) and MarkAir (bankrupt in 1995) also deserve mention as recent low-cost carriers. Together, these traditional and low-cost airlines provide the overwhelming majority of scheduled service in the United States.[3] It is the competition between traditional and low-cost carriers on common hub-to-spoke routes which is the main focus of this thesis.

2.2 Differences in Route Network

2.2.1 Hub-and-Spoke Network

All traditional airlines and at least one low-cost airline[4] organize their production of air services around a hub-and-spoke network. As

[1] A seat-mile is one seat flown one mile. Cost per available seat-mile is the standard measure of unit cost in the airline industry.

[2] Ranked by system revenue passenger-miles (RPMs) for January-May, 1995. *See Air Transport World* October, 1995: 134. A revenue passenger-mile is one revenue passenger flown one mile.

[3] One carrier not in this list is Alaska Airlines, whose operations are confined mainly to the west coast of the United States and the state of Alaska. In this paper, Alaska does not qualify for either traditional or low-cost status because it does not have a hub-and-spoke route network and its costs are too high to be considered low-cost.

[4] Western Pacific Airlines operates a hub at Colorado Springs. However, its size is far smaller than the smallest hub operated by any traditional carrier.

Figure 2.1 illustrates, a hub-and-spoke network connects passengers from many originating cities to many destination cities by means of a central "hub" airport. Each arriving aircraft at the hub carries both passengers destined for beyond cities and passengers destined for the hub city. At the hub, the beyond passengers change planes to connect to other flights[5] while the "local" passengers -- those whose final destination is the hub city -- deplane and leave the airport. Hub departures combine the connecting passengers with newly originating local passengers for flights to beyond cities.

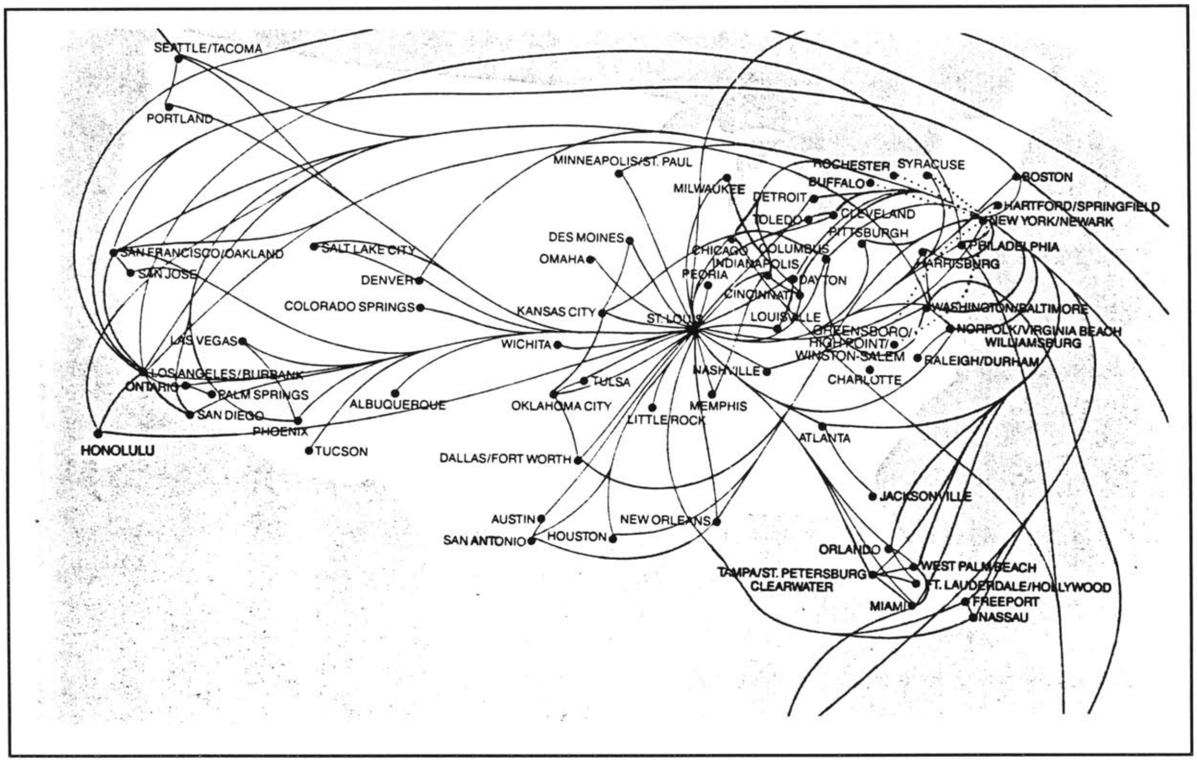

Figure 2.1: Example of a Hub-and-Spoke Route Structure: Trans World Airlines, June, 1986.

The hub-and-spoke network has many operational advantages. First, it exhibits economies of scope. That is the number of city-pairs served through the hub increases disproportionately with the number of spoke cities served from the hub. This increases aircraft load factors because each aircraft now carries passengers flying between many

[5] There are always some passengers who do not need to change aircraft because the aircraft on which they originate is routed from their city of origin to their destination. This type of service is termed "direct" or "1-stop."

different cities. Second, hub-and-spoke operations exhibit economies of scale. As load factors increase, an airline may use larger aircraft with lower per unit operating costs.[6] Additional economies of scale may be realized by the consolidation of many airline facilities and contracts at the hub airport. Facilities and contracts, which include maintenance, fuel, crew bases, catering and headquarters, entail substantial fixed costs that would be larger if scattered at different airports as in other route networks. Third, a hub-and-spoke operation engenders market power for the hub airline for passengers flying between hub and spoke cities. This occurs partly because the hub airline offers by far the greatest number of frequencies from the hub city and partly through marketing arrangements to be described in Chapter 2. Last, hub-and-spoke operations facilitate the regular and anomalous scheduling of crews and aircraft since all flights must go through the hub airport.

The main disadvantages to operating a hub-and-spoke network are the increased fuel, airport charge and aircraft utilization cost of an additional per-passenger takeoff and landing, the loss of passengers through the loss of formerly nonstop service between spoke cities (although the additional frequencies offered through the hub do counteract this), and the cost of passenger handling facilities at the hub airport. Other disadvantages to hub-and-spoke operations include vulnerability to competing carriers' nonstop flights between spoke cities; decreases in aircraft utilization and customer satisfaction from hub congestion and resulting Air Traffic Control (ATC) delays; scheduling problems to and from spoke cities located at different distances from the hub; systemwide operational disruptions due to bad weather at the hub city; and high fixed costs at the hub, which virtually cement the hub airline to its hub airport and current operational strategy.

2.2.2 Point-to-Point Network

Most low-cost airlines, including Southwest and RenoAir, operate a point-to-point network. In contrast to a hub-and-spoke network, a point-to-point network is not

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[6] In practice, however, the increase in aircraft load factors by itself is often enough to justify the establishment of a hub-and-spoke operation.

designed to move passengers efficiently through a hub between distant spoke cities. Instead, the main goal of a point-to-point operation is to provide frequent nonstop and direct service between cities whose local demand can support it. While flight connections are possible, they are only realistic at the larger cities, as the sheer frequency of flights may compensate for scheduling that does not explicitly consider connecting traffic. As Figure 2.2 shows, there is no hub city in a point-to-point operation, although some larger, more centrally located cities may have nonstops to more destinations than other cities.

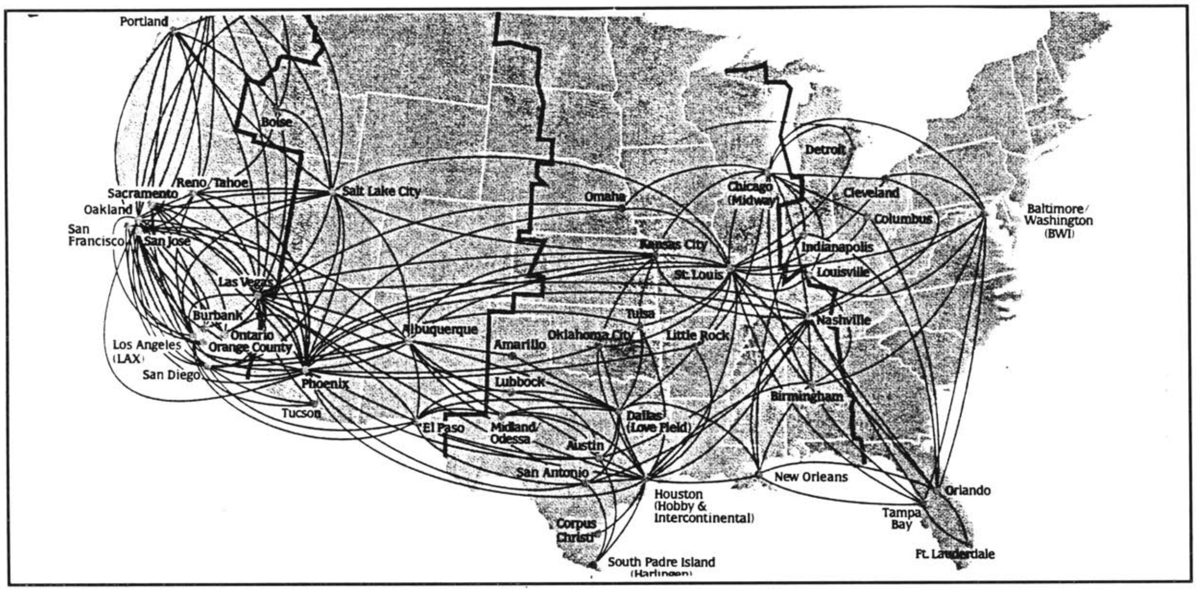

Figure 2.2: Example of a Point-to-Point Route Structure: Southwest Airlines, June, 1995.

In a deregulated environment, successful point-to-point networks are based on high aircraft utilization. High aircraft utilization cuts airline unit costs because more departures or more hours of flying are spread over fixed aircraft ownership costs like interest, hull insurance and depreciation. Thus, there is more opportunity for an airline to generate revenues and pay off these fixed costs. In the U.S., low-cost point-to-point carriers achieve increased aircraft utilization mostly through more daily departures.[7]

[7] That low-cost airlines are able to increase aircraft utilization through more departures rather than longer flights or by stretching the flying day is remarkable because one would intuitively correlate more departures with greater on the ground time and hence less flying hours. It is low-cost airlines' turnaround time that makes the difference.

Unlike airlines with a hub-and-spoke operation, who must allow minimum connecting times between arriving and departing aircraft at the hub, a low-cost airline operating a point-to-point network need only schedule enough time to turn the aircraft around for another flight -- as little as 15 minutes in some cases. Moreover, because point-to-point flights at most airports are spread evenly throughout the day, peak period airport congestion affects a much smaller portion of a point-to-point carrier's system. And, of course, there are never any late connecting flights in a point-to-point network, the effects of which often domino through the systems of hub-and-spoke airlines.

Increased aircraft utilization also helps low-cost point-to-point carriers lower airport costs. Shorter turnaround times mean that more departures can be handled with fewer gates. And a more even spacing of airport operations decreases terminal costs because less ticket counter space is required to process departing passengers.

For low-cost carriers, the main operational disadvantage of a point-to-point network stems ironically from its reason for being: the focus on local passengers means that there is little connecting traffic -- either on-line or interline[8] -- to raise load factors and not enough flights to enough destinations to confer the same kind of dominance at an airport as a hub-and-spoke carrier would gain. In reality, these disadvantages are often worse because the low-cost airline usually offers an inferior level of service to traditional airlines in the market. However, the low-cost carrier has other ways to fill seats, as will be discussed later.

2.2.3 Quasi-Hub Networks[9]

Some low-cost airlines operate networks that do not fit the standard definitions of hub-and-spoke, point-to-point or mixed. Mostly, these networks resemble hub-and-spoke

[8] On-line connections are connections on the same airline. Inter-line connections are connections between airlines. With the advent of hub-and-spoke networks, very few passengers need switch carriers anymore to complete their trip.

[9] Term used by Michael Levine, Vice President Marketing and International, Northwest Airlines, at seminar at the Massachusetts Institute of Technology, April, 1995.

networks, except that the timing of flights is designed for convenience to and from rather than beyond the hub city. Such networks are really quasi-hub, because they do not take advantage of the economies of scope and scale that a hub-and-spoke networks allows. Valujet Airlines, whose route structure is illustrated in

Figure 2.3, is one example of a quasi-hub airline. While Valujet schedules its flights through two "focus" cities (Atlanta, Washington, D.C.) like a hub-and-spoke carrier, few of the flights are timed to make realistic connections. Other Valujet focus cities (e.g. Boston, Orlando) are not in the right locations for connecting traffic; flights to and from these cities are clearly supported by local demand. Morris Air (bought by Southwest Airlines in 1994) had a route network similar to Valujet's. Although Morris Air routed almost all flights through its Salt Lake City "hub," flights departing the hub did not appear to be timed for connections. Instead, Morris schedules seemed to consider only the traffic to and from Salt Lake City.

2.3 Marketing and Service

Although traditional and low-cost airlines fly many of the same routes, their on-ground and in-flight levels of service are often very different. Traditional airlines offer such amenities as pre-assigned seating, frequent-flyer programs, first class cabins, meal service and private airport lounges. Due in part to the consolidation of traffic flows through hubs, traditional airlines also tend to fly widebody aircraft on a number of routes.[10] Passengers like widebodies because the cabin is larger and because the seats often have greater pitch.[11]

[10] Widebody aircraft have two aisles between three lengths of seats; singlebody aircraft have one aisle between two lengths of seats.

[11] Seat pitch is defined as the distance between the same point on two seats one in front of the other.

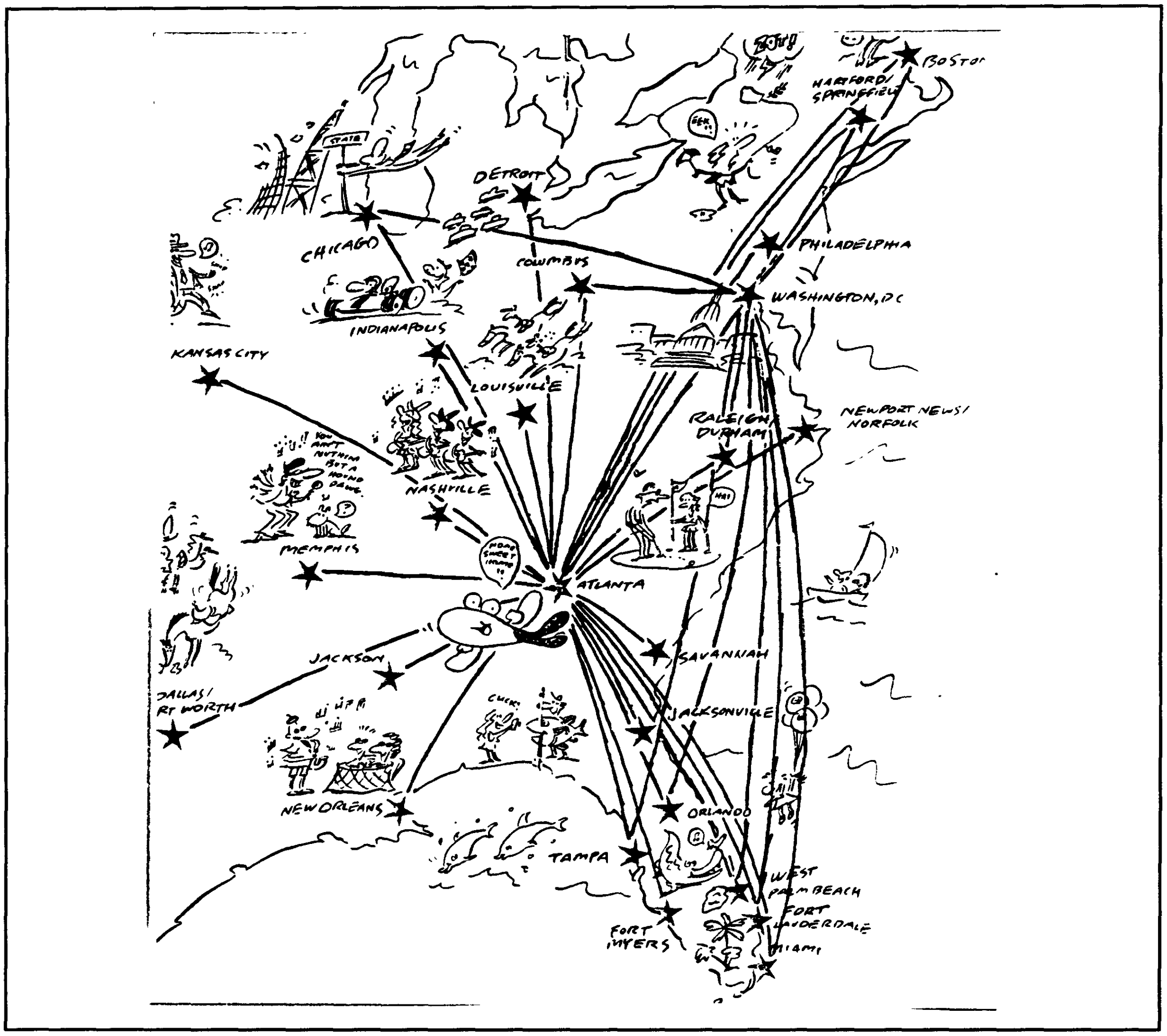

Figure 2.3: Example of a Quasi-Hub Route Structure: Valujet Airlines, October, 1995.

Low-cost airlines, by contrast, offer very limited passenger services. Most do not have pre-assigned seating, for example, because the time involved in assigning seats decreases employee productivity. Some do have frequent-flyer programs, but as free trips can only be used over the low-cost airline's rather small and circuitous route network, passengers prefer the frequent-flyer programs of traditional carriers. Meal service, first and business class cabins, private airport lounges and widebody aircraft simply do not exist.

The vast difference in level of service between traditional and low-cost airlines reflects the different types of passengers that each type of airline is trying to attract. Passengers on traditional airlines fly relatively long distances for which pre-assigned seating, meal service, first and business class cabins, frequent-flyer miles and private airport lounges become more desirable. By contrast, low-cost airline traffic tends to fly relatively short distances because connecting opportunities are poor. Moreover, traditional airlines' passengers tend to be less price-sensitive than low-cost airline passengers because their tickets are often paid for by the company for which they work or by clients; low-cost airline passengers usually pay for the ticket themselves. Other price-sensitive low-cost airline travelers are stimulated by lower fares; they would not have flown otherwise. To them, service quality is a strictly secondary concern.

2.4 Cost Structure

As mentioned in Section 1.1, low-cost airlines have unit costs far below those of traditional carriers, in most cases below $.08 per available seat-mile. In general, this means that it is cheaper for low-cost carriers to fly the same routes as traditional airlines. However, because unit costs decline with increasing stage lengths,[12] unit cost data for different airlines needs to be "corrected" for average stage length for any meaningful cost comparison. There is no easy formula to correct unit costs for average stage length; the easiest way to do it is to compare pro-rated unit costs on two routes the airlines fly in common with similar size and age aircraft.

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[12] Unit costs decline with stage length mainly because longer stage lengths are correlated with greater aircraft, labor and fuel utilization. Thus, fixed rental, depreciation and insurance costs are spread over more seat-miles. Other reasons include less frequently incurred airport charges and station costs, and a reduction in maintenance charges based on take-offs and landings.

The relationship between unit costs and average stage length is illustrated in Figure 2.4, which plots domestic unit costs versus average stage length for all traditional and some low-cost airlines for 1994. The plot shows that unit costs for the traditional airlines seem to fall on a concave curve that declines with average stage length, while low-cost airline unit costs do not seem to vary much with distance. This implies that increasing stage lengths is a viable, albeit cosmetic, way for traditional airlines to cut unit costs. However, it is more difficult to interpret the placement of low-cost airlines on the plot. Although the points show low-cost airline unit costs invariant with average stage length, there is also a clumping of low-cost airlines into three groups (WN, QQ, J7, KN;BF, HP; KP) that suggests differences in cost structure between different types of low-cost airline.

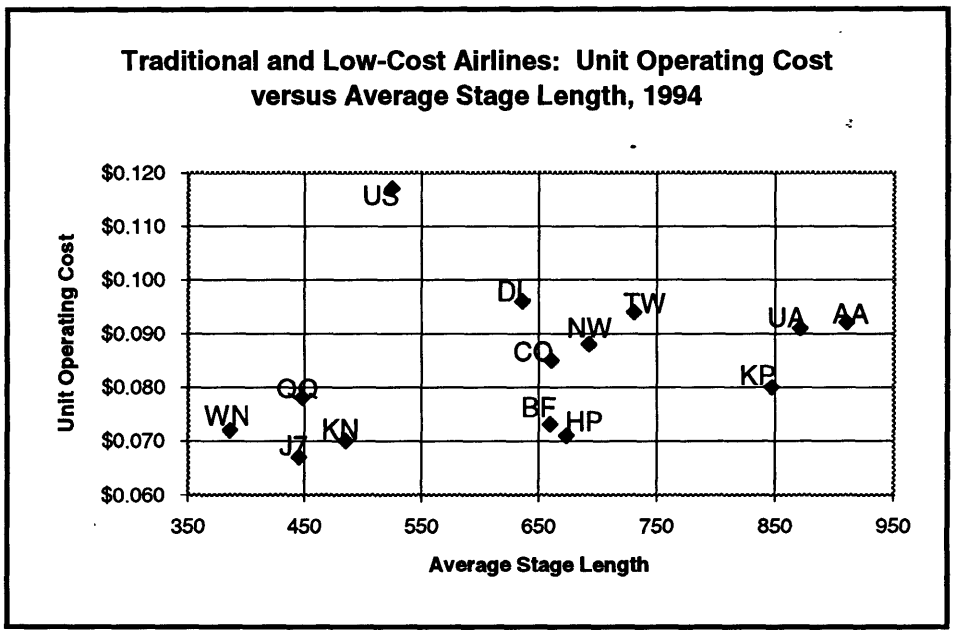

Figure 2.4: Low-Cost Carriers WN, J7, QQ, KN, BF, HP and BP have lower unit costs than traditional airlines at similar average stage lengths. (Source: Air Carrier Traffic Statistics Monthly, U.S.DOT Bureau of Transportation Statistics, 12 Months Ending Dec. 1994)

As expected, Figure 2.4 also shows that low-cost airlines that fly similar average distances as traditional airlines also cut costs in other, just as significant ways. For example, although many low-cost airlines pay pilot crews market rates, they also require more hours of flying.[13] Cabin crews are often paid by the trip rather than by the hour, eliminating pay for on-the-ground time. And because low-cost airlines often fly only one or two aircraft types, they enjoy economies of fleet commonality and size derived from more efficient use of spare parts, maintenance procedures and flight crew training. At least one low-cost carrier, Southwest, has also kept down costs by borrowing money and acquiring aircraft when they identified growth opportunities regardless of the general economic climate. This happened during the recession of 1991-1992 when Southwest expanded capacity in California and Chicago.[14]

* * *

Traditional airlines include the largest full-service, hub-and-spoke style airlines like United, Delta and American. Traditional airlines generally provide amenities like pre-assigned seating, extensive frequent flyer programs, first class cabins, meal service and private airport lounges. However, their costs are relatively high: over $.08 per seat-mile. Low-cost airlines are so named because of their low costs -- under $.08 per seat-mile. However low-cost airlines are also distinguished by their no-frills service and their price leadership in competitive markets. Examples of low-cost airlines include Southwest, Valujet and RenoAir.

[13] Of course, because low-cost airline turnaround times are so short and despite the greater number of departures, a greater proportion of flight crew salary already goes to actual flying rather than on-ground time. In fact, one of the arguments by traditional airline pilots wary of cloning low-cost operations for lower pay is that their salaries are not the problem with labor costs. Rather, it is the decrease in productivity from managment's "wasteful" use of the pilots' time (on average, about 1 hour) during hub connections that is uncompetitive.

[14] David A. Brown, "Shrewd Capital Planning Allows Southwest to Outperform Competition," *Aviation Week and Space Technology* v136 n21: 56-57.

3. Local Hub Market Competition

3.1 Definition of Local Hub Market

One consequence of the rise of hub-and-spoke route networks in the United States is that passengers with many different itineraries share space on the same flight leg. For example, the portion of a flight by a traditional airline from San Diego to Phoenix may combine passengers whose destination is Phoenix with passengers whose destinations are elsewhere, but who must connect to other flights at Phoenix to complete their journeys. In this case, the passengers whose final destinations are beyond Phoenix are "1-stop" or "2-stop" or "connecting" passengers depending on any plane changes they must make at Phoenix and elsewhere. The passengers who originate their flights in San Diego and fly nonstop to their final destination, Phoenix, are "local" passengers. Similarly, passengers who originate their travel at Phoenix and fly nonstop to San Diego are also local passengers.

Local passengers who fly either direction between an airport at which a traditional airline hubs and an airport connected by the traditional airline to that hub are "local hub passengers." Although there is no reason not to distinguish between local hub passengers who originate at the hub and local hub passengers who originate at the spoke (indeed, such passengers may have significantly different characteristics), it is common to group local hub passengers bi-directionally into the "local hub market." In the example above, because America West Airlines hubs at Phoenix, the Phoenix-San Diego bi-directional origination and destination (O&D) market is one local hub market (Figure 3.1).

Local hub market passengers play different roles within different route networks. In a hub-and-spoke system, for example, local hub passengers are important because they fills empty seats left after higher revenue connecting traffic has been accommodated. The number of these empty seats is not trivial. Some hubs, like America West at Phoenix, may rely on passengers whose origin or destination is the hub city for as much as 50% of total enplanements. Other hubs, like Delta Air Lines at Cincinnati, count relatively few local passengers among the enplaned. Most hub-and-spoke airlines, however, enplane at least 30-35% of total hub passengers as local, which is far more than enough to decide the viability of a hub if competitors for local passengers threaten.

If local traffic[15] plays an important role in a hub-and-spoke route network, its role in a point-to-point network is critical. As discussed in Chapter 2, point-to-point networks target geographically close medium-to-large size cities with strong enough economic links to support frequent nonstop and direct service. Thus, on another flight from San Diego to Phoenix, but provided by a low-cost airline with a point-to-point network, over 65% of the passengers may be local -- as opposed to 35% for the hub-and-spoke carrier. Conversely, about 35% of the point-to-point airline's traffic will be direct or connecting (but mostly direct). On average, then, the percentages of the types of passengers on a traditional versus a point-to-point airline flight on the same hub-to-spoke route are roughly opposite. In some instances, this limited overlap of passenger type is part of what allows a low-cost carrier to successfully share the traffic with a traditional carrier at a traditional carrier's hub airport.

[15] In airline parlance, the words "traffic" and "passengers" are synonymous.

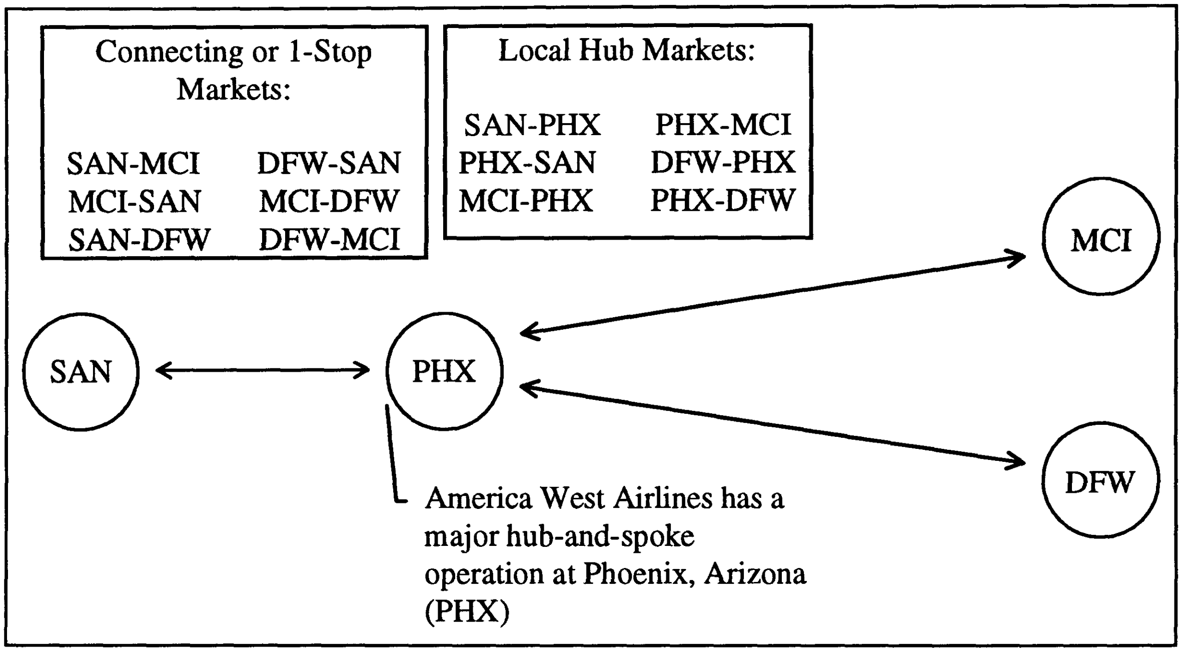

Figure 3.1: Comparison of Local Hub Markets and Connecting and 1-Stop Markets. Passengers traveling between San Diego (SAN) and Kansas City (MCI) or Dallas/Ft. Worth (DFW) must stop in Phoenix and possibly change planes to reach their final destination.

Local passengers are at least as important to low-cost airlines with quasi-hub networks as with point-to-point networks. The selection of so-called "focus cities" by quasi-hub carriers implies that there is strong enough local traffic demand at these cities to support flights to a wide array of destinations. In fact, because connecting opportunities are so poorly timed at the more centrally located focus cities, the percentage of local traffic on quasi-hub airline flights might be even higher than on hub to spoke flights operated by a point-to-point airline. This makes attracting local traffic an even higher priority.

3.2 Airline Choice in Local Hub Markets

3.2.1 Major Choice Variables

3.2.1.1 Airfares

The fare, or price, that must be paid for a ticket is the most important determinant of airline demand. An airline faces two major constraints when pricing its seats. First, it must consider the reaction of market demand. For example, the number of local passengers who want to travel between San Diego and Phoenix on any airline depends on the level of fares in the market. Second, it must consider the fares being charged by its competitors. Indeed, because there is little *prima facie* difference between a seat on two different airlines for the same service between the same two cities, many air travelers will choose the airline with the lowest fare. This puts tremendous pressure on competing airlines to match each other's fares, and gives a big advantage to the airline with lower costs, who usually becomes the price leader in the markets it serves.[16]

All airlines offer multiple fares in the same market. As a rule, these fares are the same in value and conditions for all carriers. However, willingness to pay a particular fare depends mostly on the characteristics of the intended passenger trip. In general, passengers on "business" trips -- trips related to personal or company business and planned within a week of the flight -- are willing to pay higher fares because the additional expense of the trip is small compared to the money to be lost by not making it. Thus, variation in the price of business-type fares does not have much effect on the number of business passengers.

On the other hand, passengers on "leisure trips" -- trips made for vacation or to visit friends or relatives, and planned weeks in advance -- will not pay fares as high as passengers on business trips because leisure passengers usually pay for tickets out of their

[16] The term "price leader" refers to a firm that sets the price in a market, which other firms than take as given.

own pocket and have a limited travel budget.[17] Thus, variation in the price of leisure-type fares has a larger effect on the number of leisure passengers. Of course, most passenger trips fall along a trip purpose "continuum" and the passengers on them are willing to pay fares somewhere in between these business and leisure extremes.

Because passengers with differential willingness-to-pay tend to buy tickets for the same flight at different times before departure, airlines have used differential pricing as a way to maximize revenue. Typically, the fares airlines make available increase as time to flight departure approaches. This way, the airline can charge later-booking business passengers a higher price than earlier-booking vacationers with little chance that business traffic will be able to qualify for the lower fares.[18] Because a business traveler in a short-haul market (less than 750 miles) may pay as much as four times as much as a leisure traveler for what is essentially the same seat,[19] it is extremely important that airlines adopt fare restrictions like advance ticket purchase deadlines to properly segment business from leisure passengers.

3.2.1.2 Flight Frequency

The demand for air travel is derived from the demand for activities at the destination city or in the destination region. Because there is only a certain amount of time during which to take advantage of these activities, potential air travelers usually have a time window during which they are willing to fly. This time window is narrowed by constraints at the origin such as work, school or family obligations.

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[17] Most business trips are paid for by the company for which the passenger works, or are billed directly to clients.

[18] Airlines also use other methods to separate traffic based on perceived willingness-to-pay. For example, most leisure passengers do not mind staying over Saturday night at their destination, while most business passengers -- many of whom have families and/or other obligations at home -- abhor the idea. Thus, tickets with a Saturday night stay restriction are another way to separate business from leisure traffic.

[19] Based on the author's own observations of the highest and lowest fares charged by America West in the Phoenix-San Diego market for much of 1995. The highest unrestricted fare was $159 and the lowest restricted fare $39.

The size and placement of a potential air traveler's time window varies according to the purpose of the trip. Business passengers have a very narrow time window because the activities at their destinations must take place on certain dates or the company loses customers or money. Leisure passengers, including those traveling on vacation and those visiting friends and relatives, usually have a much broader time window because there is no date by which they have to make the trip to avoid "unpleasant" consequences. Their plans are much more flexible.

An airline with greater flight frequencies is more likely to have a flight or a set of flights within a potential air traveler's time window. Assuming that most service on a route is symmetric (i.e. there are an equal number of flights in both directions), the airline with more frequenices in one direction will also have more frequencies in the other. Because passengers almost always choose their outbound and inbound flights together, and because they prefer to use the same airline for both flights (to accumulate frequent-flyer mileage more rapidly or to be near their parked car upon return, for example), there is a thus a disproportionate advantage to the airline with the most frequency on a route, all else equal. In other words, the airline with higher frequency obtains market share greater than its frequency share.

Figure 3.2 illustrates the disproportionate market share versus frequency share relationship for a hypothetical two-airline nonstop market and a factor of proportionality equal to 1.7. (The exact equation for this market share verus frequency share relationship is $MS_i = FS_i^{1.7} / \sum_j FS_j^{1.7}$. It reads "the market share for airline i is equal to the frequency share for airline i rasised to the 1.7 power, divided by the sum of the frequency shares for airlines i and j both raised to the 1.7 power.) Also drawn is the straight line relationship that would exist if market share equaled frequency share. As the so-called "S-curve" shows, the airline with under 50% frequency share suffers a disproportionate loss in market share to the airline with over 50% frequency share. Thus, frequency additions by one airline are likely to decrease load factors on the other airline at a very fast rate,

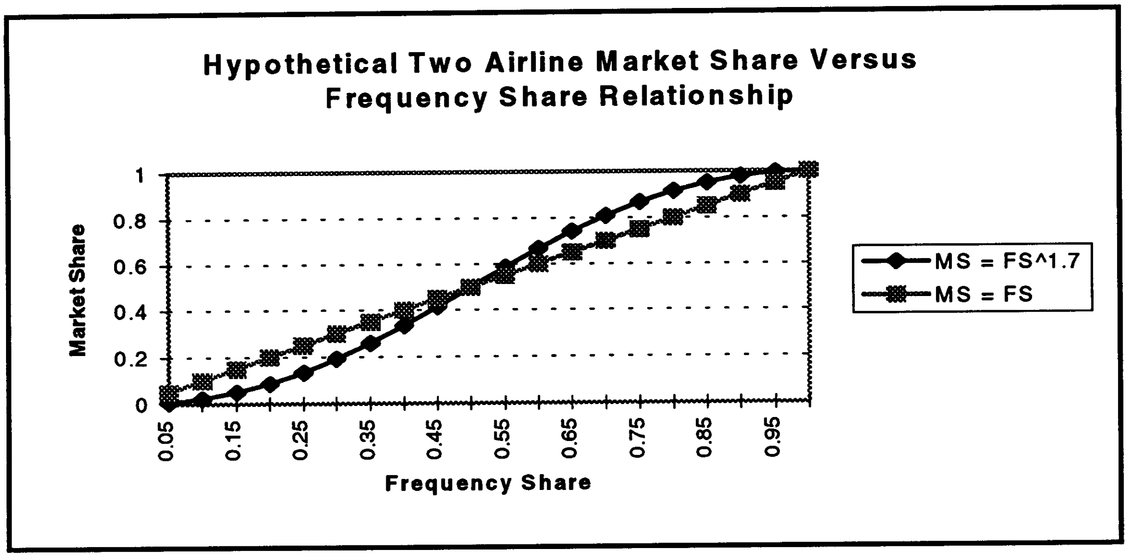

Figure 3.2: The airline with greater frequency share gains a disproportionate market share, relative to the case where market share equals frequency share. Thus, increases in frequency by the higher frequency airline can empty the seats of the lower frequency airline at a very fast rate. (Source: Notes for Course 16.74 - Air Transportation Economics, Massachusetts Institute of Technology, Fall 1994.)

unless the other airline matches the additional frequencies.

In a deregulated environment, the hypothetical market share versus frequency share relationship in Figure 3.2 seldom exists. In fact, almost every factor assumed equal between airlines in the classic S-curve relationship -- fares, service, image, aircraft size and others -- may be different in reality. For example, the low-cost airline may have more seats available at lower fares than the traditional airline in the same local hub market. Intuitively, this would tend to accentuate any frequency share advantage held by the low-cost airline, or, conversely, cushion its loss of market share should it have less frequencies than the traditional airline. On the other hand, through pre-assigned seats, frequent-flyer awards and in-flight snacks, meals and movies, the traditional airline probably has better service quality in the minds of potential air travelers. This would tend to cause the same effects for the traditional airline as lower prices do for the low-cost airline.

One last assumption of the hypothetical S-curve relationship is that passenger demand is constant and zero-sum. If one airline in a two-airline market adds flights, it takes all additional passengers from the other airline. In reality, adding flights on a route also stimulates demand, because the new set of flights will cover more potential air travelers' time windows.[20] Thus, if one airline adds flights, it will steal market share from the other airline, but it will also carry new passengers that did not fly in the past. This will make the S-curve even more pronounced, because the higher frequency airline captures an even more disproportionate share of the passengers already in the market, plus all the new passengers stimulated by its additional flights. Alternatively, if both airlines add flights, their market shares will stay about the same but they will both carry more passengers. However, whether additional flights are economically justified depends on competitive considerations such as the magnitude of the load factor gain, the average fares in the market and the importance of the market to the airline's route network.

3.2.1.3 Airline Preference

Most people who fly more than a few times per year prefer to fly certain airlines. Pricing and flight frequency are two reasons already discussed. If the traveler's experience is that one airline usually has the lowest fares, for example, he may contact that airline first to reserve a flight. Similarly, if the traveler's experience is that one airline has had the most flights to the most cities to which he has traveled in the past, he may call that airline first. In many cases, a traveler will compromise between the fare he must pay and the time at which he wants to fly.

Travelers may also choose an airline based on its real or perceived on-ground and in-flight level of service. Important airline service offerings include pre-assigned seats, first-class cabin, in-flight movies and meals, airport clubs and widebody aircraft. Some

[20] Additional demand is stimulated up to a "saturation" frequency, after which the increase in new demand is negligible. Adding another flight after satuation frequency is reached will cause market share gains to be zero-sum, although if the new flight does not provide another attractive departure time, the increase in market share may come at the expense of lower load factors. (Source: Simpson and Belobaba, 16-17.)

travelers will not fly an airline if it means taking a non-jet flight; others will not fly if that airline has had major accidents in the recent past.

Airline marketing innovations such as frequent-flyer programs have been a very successful way to build brand loyalty. Frequent-flyer programs award such items as free trips, first-class upgrades, dedicated check-in and reserved window and aisle seats to their members based on accumulated mileage. Although most airlines establish the same mileage levels for similar awards, the awards themselves increase disproportionately with incremental mileage. This encourages members to concentrate travel on fewer airlines because instead of acquiring, say, 40,000 miles each on two airlines, they can acquire 100,000 miles (and the extra awards) by flying only one.

There are also ways to influence airline choice that are hidden from the traveler. For example, airlines encourage travel agents (who sell approximately 80% of airline tickets) to steer customers towards their flights by offering commission overrides for bookings taken or tickets sold in certain markets above some target level.[21] As with frequent-flyer awards, commission overrides increase disproportionately with additional sales after the target level is reached. The standard commission rate of 10% can quickly reach as high as 40% for the incremental sales.[22]

Airlines can also induce bias into travel agent flight selections through the airline-owned computer reservations systems (CRSs) that travel agents use. Although the United States Department of Justice has discovered and prohibited the most egregious abuses of CRS ownership (for example, algorithms that always list the airline owning the CRS first even when that airline does not provide the most convenient departure time), it is unclear to what extent airlines are still able to use CRS's to influence travel agent behavior.

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[21] Alfred E. Kahn, "The Competitive Consequences of Hub Dominance: A Case Study," *Review of Industrial Organization* August 1993: 381-405.

[22] Kahn, 381-405.

3.2.1.4 Role of Connecting Traffic and Yield Management Systems

Although all airlines offer the same fares in a market, the availability of a particular fare for a particular flight may depend on the value of and demand for other fares that may compete for seats on that flight. The necessity of keeping track of the demand for different passenger itineraries sharing the same flight leg but worth different revenue values to an airline's network has led to the development and continuing improvement of airline yield management systems. By forecasting the demand for different fare types on a flight, setting limits on the number of reservations taken for all but the highest fares and adopting heuristics for special cases,[23] yield management systems are designed to maximize an airline's network revenue.

The yield management systems of all traditional and some low-cost carriers prioritize reservation requests according to the fare value the requests represent. Such yield management systems are called "revenue stratified." Because requests for connecting itineraries usually represent higher fares, revenue-stratified yield management systems give higher priority to connecting fare requests. This means that the yield management system saves seats for potential connecting traffic first, allocating the remaining seats to local fare/itinerary requests. The result is that depending on the variability of demand for a particular flight leg, the airline may refuse reservation requests by local traffic some of the time if the demand for connecting itineraries is especially high.

Differences in higher fare demand are the main reason why a potential traveler may call two different airlines for a reservation and be quoted two different fares. The fare on the flight that does not expect as much connecting or local business traffic will be lower than the fare on the flight that does expect more higher fare demand. If the potential traveler wants a seat on the higher demand flight, he will be forced to pay a fare

[23] For example, the sum of two individually cheaper local fares is generally higher than the corresponding connecting fare, so it makes sense to refuse a request for the itinerary using the connecting fare if enough local demand exists to fill the remaining seats on both flight legs. Actually, the ability to refuse a higher revenue connecting itinerary request for two local itinerary requests is a feature of so-called bid price systems which most carriers do not yet own. The example is only used here for illustrative purposes.

comparable to the fare that the higher demand flight would lose if it accepted a local reservation at the lower fare offered on the lower demand flight.

3.2.2 Market Segmentation

When a traditional airline competes with a low-cost airline in the same local hub market, conventional wisdom says that the traditional airline's strength of schedule, superior frequent-flyer program, better on-ground and in-flight level of service, travel agent dominance and name recognition allow it to capture the majority of the higher-paying business traffic while the low-cost airline, with its no-frills approach, carries mostly lower-fare leisure-type passengers. In a recent magazine article, for example, executives of several low-cost airlines boldly stated that there is no overlap at all between the traffic on their flights and the traditional airlines' passengers.[24] "We're bringing passengers back to the airport," one executive said. "We stole people from their living rooms and automobiles."[25] True, many executives at traditional airlines may reply. But because airlines operate as if two seats for the same flight on two different airlines are close substitutes -- regardless if one airline is traditional and the other low-cost -- traditional airlines may keep their passengers but at much lower fares than if the low-cost competition did not exist.

However, if traditional and low-cost airlines do, in general, carry different segments of the local traffic market, then the differential valuation each airline's customers place on certain transport supply variables should be empirically testable. For example, does an additional flight stimulate more passengers for the traditional or low-cost airline ? Although Chapter 5 focuses on the actual generation of such local hub market demand models, it will help the analysis later if some differential expectations for the effects of the most fundamental transport supply variables on passenger demand are stated now.

[24] Paul Gray, "How High Can They Fly?" *TIME* April 22, 1996: 68-70.

[25] Quote by Lewis Jordan, President of Valujet Airlines in *TIME* April 22, 1996: 68-70.

First, low-cost airline passengers should be much more sensitive to changes in fare. By their executives' own admission, low-cost airlines stimulate most of their passengers through fares much lower than those offered by traditional airlines. These are passengers who would have taken other modes of transportation or even stayed home had these fares not existed. They are much more flexible in the plans they make.

By contrast, the number of traditional airline passengers should be less price-sensitive. A local traffic base weighted towards business-type passengers implies that the most trips will occur regardless of the fare. A large decrease in the amount business travelers must pay for an airline seat will translate mainly into a large decrease in revenue because very little traffic will be stimulated.

Second, traditional airline passengers should be more sensitive to changes in the number of flights. The hypothetical S-curve relationship is even more pronounced when only higher-fare business traffic is considered. This occurs because business traffic is very time-sensistive; thus, it tends to always fly the carrier with the most flights. Also, business traffic is unlikely to switch to a more inconvenient flight time for a cheaper fare. And because business traffic pays higher fares, it is given better seat availability than lower-fare leisure traffic. Low-cost airline passengers, on the other hand, are not as concerned about the times at which they fly. They will gladly accept a less desirable flight time in exchange for a markedly lower fare.

Third, traditional airline passengers should be much less sensitive to changes in the fares and flight frequencies of the low-cost airline. Through its superior level of service and name recognition, the traditional carrier should be preferred in markets where both types of airline compete, all else equal. Many of the traditional airline's passengers will only fly the traditional airline; however, low-cost airline passengers are probably at worst indifferent between the two. This implies that the traditional airline can sustain some level of fare and/or frequency premium against the low-cost airline. For example, more passengers might be willing to pay an extra 10% for a traditional airline ticket than for a ticket on a low-cost carrier. Also, if the traditional airline dominates the number of local hub flights, an additional low-cost carrier flight is not likely to generate more traffic than if the traditional airline adds another flight and is able to accommodate passengers who take a low-cost airline flight only because the traditional airline flight is already full.

Preference for the traditional airline should be especially strong by passengers who begin their trips at the hub airport. (Recall that a local hub market includes passengers originating their trips either at the hub <u>or</u> the spoke airport.) This is because frequent-flyer programs, travel agent commission overrides and CRS bias are especially effective in securing originating traffic for the traditional airline at its hub city. Frequent travelers from the hub city are likely to be members of the frequent-flyer program of the hub carrier since it offers the most flights to the most destinations, while travel agents tend to affiliate with and sell tickets on the hub carrier because its commission overrides and other promotions generate the most revenue.

The advantage these marketing arrangements confer on the dominant hub-and-spoke carrier for local hub traffic can be large, at least for competition between traditional carriers only. One study that compared the traffic shares of the two largest airlines in Chicago, American and United, found that although United had only 14% more flights than American, it captured about 64% more passengers whose trips originated in Chicago. The study found that this difference far exceeded the traffic difference that would be predicted on the basis of the relative service offerings of the two carriers. Along with the higher average fare paid by United Airlines passengers, United's 14% flight frequency advantage translated into an enormous revenue advantage of nearly 69%![26]

* * *

The competition between traditional and low-cost carriers for local hub traffic is played on many levels. Although most passengers are initially biased towards choosing the traditional carrier, factors like fares, flight frequency, airline preference and even point

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[26] Kahn, 381-405.

of origin are more significant determinants of passenger airline choice. However, traditional and low-cost airlines do tend to attract passengers with different and distinct characteristics. This implies that estimating local hub market demand models for traditional and low-cost carriers should produce statistically different coefficient values for the same explanatory variables used to describe each type of airline's passengers. The process of creating such models is the subject of Chapter 4.

4. Modeling Local Hub Market Demand

4.1 Overview of Previous Research

Although the air travel demand modeling literature is extensive, its primary focus has been on modeling origin and destination traffic in the largest or in a wide variety of U.S. city-pairs. There does not seem to be any study which attempts to isolate and explain origin and destination traffic between a hub and its spoke cities. Moreover, because more than two airlines may offer competitive service (including difficult to model connecting flights) in large U.S. city-pair markets, it has been impractical to consider how changes in the service level offerings of one carrier may affect the traffic of other carriers.

Despite the lack of studies that focus explicitly on local hub market demand modeling, the literature provides important insights into the functional form and specification that a local hub market demand model should take. Because passenger demand in local hub markets is, by definition, for transport between the hub and spoke or spoke and hub city, it seems appropriate to use city-pair models to explain local hub market demand. City-pair models postulate that the demand for travel between cities A and B is a function of a vector of socioeconomic variables each for city A and B, and a vector of transport supply variables for the transportation system connecting them:[27]

$$T_{ij} = T(D_i, D_j, S_{ij}) \tag{4.1}$$

where

T_{ij} is the number of passengers between cities i and j

D_i is a vector of socioeconomic variables for city i

D_j is a vector of socioeconomic variables for city j

[27] Adib Kanafani, Transportation Demand Analysis (New York: McGraw-Hill, Inc., 1983) 256.

S_{ij} is a vector of transport supply variables between cities i and j.

In practice, when total two-way market demand is measured, as in this thesis, the socioeconomic variables for cities i and j are treated the same and references to one or the other city as the origin or destination are dropped.[28]

For airline city-pair demand modeling, the most often used types of socioeconomic variables are population, employment and per capita income. The most important transport supply variables include airfares, travel time, flight frequency, aircraft size and type. If demand for a particular carrier relative to another is being modeled, then other carrier-specific attributes such as frequent-flyer programs and local travel agent influence may have to be considered.

In the air travel demand literature, most city-pair models assume the number of passengers is a multiplicative, rather than an additive, function of the socioeconomic and transport supply variables.[29] There are two benefits to modeling demand in this way. First, the multiplicative form allows for greater interaction between the explanatory variables. Second, the coefficients in a multiplicative demand function are the elasticities of demand with respect to the explanatory variables. Constant elasticity functions are popular in demand modeling because they seem to "fit" empirical data very well.

Belobaba and Simpson developed a very simple air travel demand function for a market with only one carrier and a single class of on-board service. The equation relates demand to a market sizing parameter, which serves as a proxy for variables like population and per capita income, and three transport supply variables: airline "image" (a proxy for

[28] Kanafani, 256.

[29] Peter B. Belobaba and Robert W. Simpson, Notes for Air Transportation Economics, (M.I.T. Department of Aeronautics and Astronautics Course 16.74, Fall, 1994) 11.

qualitative attributes like perceived reliability, comfort and safety), airfare and total travel time:[30]

$$D = M \cdot I \cdot T^{B} \cdot P^{\alpha} \tag{4.2}$$

where

D	is total market traffic
M	is a market sizing parameter
I	is the airline image factor
P	is the average fare paid
T	is total <u>door-to-door</u> travel time
α	is the price elasticity of demand
B	is the time elasticity of demand

There are several important features about Equation 4.2. First, the lack of elasticities[31] for market size and image factor imply that these terms are constant. In reality, over time or across markets, meaningful elasticities can be calculated for such variables. Second, the coefficients in a multiplicative demand model are actually the elasticities of each variable relative to total demand. As with slope measurements in a linear model, these elasticities are assumed constant over the full range of values for the explanatory variables. Third, Equation 4.2 is admittedly a simple model that does not include many socioeconomic and transport supply variables whose individual effects on demand are empirically useful and interesting. Moreover, because demand prediction is limited to a market with a single carrier, the model does not offer a way to account for the effects of competitors' service offerings in non-monopoly markets.

[30] Belobaba and Simpson, 12.

[31] Elasticity is formally defined as the percent change in the dependent variable due to a 1% change in one of the explanatory variables, <u>holding the values of all other explanatory variables constant</u>. In mathematical notation, Elasticity of variable y with respect to variable x ($E_{y,x}$) = (dY/dX)(X/Y).

The extensive literature on air travel demand modeling offers some insight into the types of socioeconomic and transport supply variables that should and should not be included in a more comprehensive airline demand model. For example, Talley and Eckroade calibrated a passenger traffic model for Piedmont Airlines' 1979 and 1980 monopoly flight segments using such explanatory variables as fare per mile, flight frequency, load factor and aircraft size.[32] They were surprised to find, however, that only flight frequency was consistently statistically significant at a 5% level.

Upon reflection, this does not seem so unusual. All else equal, both fare per mile (also known as airline yield) and passenger demand decrease with distance, so the clear negative effect of yield on demand for markets about the same distance apart was probably counterbalanced by the positive correlation between yield and demand as market distance increases. Talley and Eckroade also believed airline load factor to have a negative effect on demand, because as a flight segment's average load factor increases, the likelihood that a passenger may not be able to reserve a seat on his preferred flight also increases. However, it is intuitively obvious that as an airline's load factor increases, so does the number of passengers it carries; in fact, regressing traffic on load factor is much like regressing traffic on itself. The only time that increased load factors may have a negative effect on the amount of traffic in a market is when capacity is decreased, and in that case the decrease in aircraft size better explains the traffic loss than the resulting increase in load factor.

Recently, Ghobrial and Kanafani proposed a comprehensive model of air travel demand for the top 100 U.S. airport pairs. The model is notable both for its size (it includes 10 variables) and because some variables that are usually treated in an aggregate sense, such as flight frequency, are split according to pre-defined peak and off-peak times of day. The model is specified as:[33]

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[32] Wayne K. Talley and William R. Eckroade, "Airline Passenger Demand in Monopoly Flight Segments of a Single Airline Under Deregulation," Transportation Journal Winter 1984: 73-79.

[33] A. Kanafani and A. Ghobrial, "Quality-of-Service Model of Intercity Air-Travel Demand," Journal of Transportation Engineering Vol. 121, No. 2 March/April 1995: 135-140.

$$T_{ij} = \alpha \cdot P_{ij}^{\beta} \cdot I_{ij}^{\nu} \cdot FR_{ij}^{\phi} \cdot FP_{ij}^{\mu} \cdot FO_{ij}^{\eta} \cdot SP_{ij}^{\lambda} \cdot SO_{ij}^{\varphi} \cdot TM_{ij}^{\sigma} \cdot exp(\omega TR_{ij} + \psi HUB_{ij}) \cdot \varepsilon \tag{4.3}$$

where

T_{ij} is daily passenger demand who fly directly in market ij

P_{ij} is the product of the populations of cities i and j

I_{ij} is the product of income per capita of cities i and j

FR_{ij} is the weighted average airfare by class type in market ij

FP_{ij} is the number of peak period daily flights between city-pair ij

FO_{ij} is the number of off-peak daily flights between city-pair ij

SP_{ij} is the weighted average aircraft size during peak periods between city-pair ij

SO_{ij} is the off-peak weighted average aircraft size between city-pair ij

TM_{ij} is the average travel time in hours between city-pair ij

TR_{ij} is a dummy variable for tourist markets in Florida, Hawaii or Las Vegas

HUB_{ij} is a dummy variable for capacity-constrained airports (e.g. LaGuardia)

Calibration of the above model yielded some interesting results. First, even with ten variables and under alternative specifications, the above model was never able to explain even half of the variation in city-pair traffic. Second, and far more relevant to this thesis, only the more fundamental transport supply determinants of airline city-pair traffic (i.e. airfare, flight frequencies and travel time)[34] were found to be significant at the 5% level. Thus, while the aircraft size variables had the expected signs, their values were not

[34] The dummy variables were significant in one of the three model specifications.

statistically different from zero. Apparently, passenger spill[35] is not great enough at average U.S. carrier load factors to significantly affect the total amount of city-pair traffic.

4.2 Introduction to Competitive Scenarios

4.2.1 Modeling Procedure and Considerations

4.2.1.1 General

In Chapter 5, O&D demand models are developed for the traditional carrier, low-cost carrier, and total market in three actual local hub market scenarios: Delta Air Lines (DL) versus Morris Air (KN)/Southwest Airlines (WN) at Salt Lake City, Utah (SLC);[36] America West Airlines (HP) versus Southwest Airlines at Phoenix, Arizona (PHX); and Delta Air Lines versus Valujet Airlines (J7) at Atlanta, Georgia (ATL). As explained in the introduction, the three competitive scenarios were chosen because the type and level of competition between traditional and low-cost carriers is different at all three hub airports and it should be instructive to calculate and interpret differences in elasticity estimates both within and between individual case studies. Although calibration of traditional and low-cost carrier demand models are the main purpose of this thesis, market demand equations are also estimated to see the relative effects of the traditional and low-cost carrier on market elasticities.

In all scenarios, the dependent variable is the total two-way quarterly O&D passengers who flew between cities i and j. As in the literature, the number of passengers, or PAX, is modeled as a multiplicative function of a number of socioeconomic and transport supply variables (Table 4.1). For each scenario, these variables include POPULATION, the quarterly population of the spoke city; PERCAPITA, the quarterly

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[35] Spill is defined as a refused reservation request. When average load factors are high, the variability in day-to-day load factor means that on some days a flight reaches the limit on the number of reservations it is able to accommodate. When this limit is reached, all further requests are denied.

[36] Delta competed with Morris Air at SLC until the fourth quarter of 1994 when Southwest Airlines bought Morris Air and assumed its SLC routes. Before then, Southwest did not service SLC.

Table 4.1: Explanatory Variables Used in the Demand Models

Explanatory Variable	Variable Type	Description
POP	socioeconomic	population of spoke city
PERCAPITA	socioeconomic	per capita income of spoke city
FARE	transport supply	quarterly two-way average fare paid, excluding free frequent-flyer awards
NSFREQ	transport supply	quarterly two-way nonstop flights offered
FLTTIME	transport supply	average nonstop flight time

per capita income of the spoke city; FARE, the average two-way quarterly O&D fare paid; NSFREQ, the number of two-way quarterly nonstop frequencies; and FLTTIME, the average scheduled gate-to-gate time in minutes between the hub and spoke city. (Please see Appendix A for a description of data sources and for the exact procedure used to derive each of these variables.)

Although it is not used in the demand models, an endpoint dominance variable was considered to help explain the difference in local hub market demand between traditional and low-cost carriers. Endpoint dominance is a catch-all phrase for the more or less unobservable effects that frequent-flyer programs, travel agent commission overrides, CRS dominance and carrier advertising have on passengers' airline choice in the hub and spoke city. In the literature, endpoint dominance has usually been calculated as the sum of the total originating carrier passenger shares at each endpoint airport, weighted by the percent of traffic in the market originating at each endpoint airport.[37]

Although this definition of endpoint dominance seems to be sufficient when comparing traffic between two or more traditional carriers, it does not seem like it would adequately explain the difference in local hub market demand between a traditional and

[37] See, for example, Amy Abramowitz and Stephen Brown, "Market Share and Price Determination in the Contemporary Airline Industry," *Review of Industrial Organization* 1993: 419-433.

low-cost carrier. For example, Southwest Airlines has a lot of flight frequency to and from Phoenix, and enplanes a large proportion of the passengers there. However, its inferior frequent-flyer program and lack of nonstop destinations compared to America West, the traditional hub carrier in Phoenix, implies that America West should clearly have a larger endpoint dominance advantage. But a proxy of relative enplanement shares would probably give both carriers equal weight in Phoenix. Also, it seems that there should be some lag structure to any endpoint dominance variable because it takes time for passengers to realize and respond to the effects of more flights and more nonstop destinations for a given carrier. Because the endpoint dominance variable is so difficult to define for local hub market competition, it is not used in the demand models in this thesis.

Using the set of fundamental variables defined above, this thesis estimates the same nine demand models for each carrier and set of markets for each competitive scenario (Table 4.2). The reason for the large number of demand models, which start with a single explanatory variable -- FARE -- and generally become more complex, is not because each one of them may be the *a priori* "best" model for some carrier or set of markets in one of the scenarios. Rather, they are an attempt to explain, in an increasingly more detailed manner, the differential coefficients of the carriers and set of markets. By adding explanatory variables in a more or less stepwise manner, it is possible to see the stability and range of the differential coefficient values across many realistic demand models.

The type of markets considered in each scenario are also constrained to avoid some of the previously discussed limitations of applying existing air travel demand studies to local hub market demand modeling. First, while the air distance between hub and spoke cities is in almost all cases less than 750 miles, it is also great enough to ensure that other modes of transportation do not provide effective competition. This eliminates the need to include the attributes of other transportation modes in the demand models. Second, for each quarterly market observation, the combined market share of the traditional and low-cost carriers is above 90% for SLC and PHX and above 80% for ATL.[38] Assuming that all passengers who fly the traditional or low-cost carrier between the hub and spoke fly nonstop, the market share restriction isolates those markets for which the overwhelming majority of passengers flew either the traditional or low-cost carrier nonstop. This is an attempt to ensure that the demand models will not display specification bias due to omitted variables.

4.2.1.2 Combining Cross-Section and Time-Series Data

For each local hub market scenario, demand models are calibrated using data across 11 to 12 markets[39] for the second quarter of 1993 through the second quarter of 1995.[40] Combination of cross-section and time-series data in demand estimation is not very common because cross-section coefficients may not stay constant over time. Blind estimation of such a pooled model may involve specification errors which challenge the model's coefficient estimates. Rather than obtain questionable coefficient estimates, the authors of most air travel demand studies in the literature have chosen to use only cross-section data to calibrate their models, although some have performed separate estimations over more than one year.[41]

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[38] A smaller combined market share is acceptable for ATL because the greater density of traffic in the eastern and south-eastern U.S. relative to the western U.S. means there are many more viable connecting opportunities over the same market distance.

[39] The number of markets included in the demand models is 12 for SLC, 11 for PHX and 12 for ATL.

[40] Technically, the data for each scenario comes from a combination of quarters within the given range. For SLC, the data comes from the fourth quarter of 1993 through the second quarter of 1995. For PHX, the data comes from the second quarter of 1993 through the second quarter of 1995, except for the third quarter of 1993. The ATL data comes only from the first quarter of 1994 through the second quarter of 1995. In addition, any quarterly market observations that did not have the requisite combined traditional and low-cost carrier market share were excluded from the estimation process. Thus, some markets had more quarterly observations than others.

[41] For example, Talley and Eckroade, 73-79.

Table 4.2: Demand Model Taxonomy

Model	Explanatory Variables
1	FARE
2	FARE, POPULATION
3	FARE, POPULATION, PERCAPITA
4	FARE, POPULATION, PERCAPITA, NSFREQ
5	POPULATION, PERCAPITA, NSFREQ, FLTTIME
6	FARE, POPULATION, PERCAPITA, NSFREQ, FLTTIME
7	POPULATION, PERCAPITA, DL or HPFARE, KN or WN or J7FARE
8	POPULATION, PERCAPITA, DL or HP NSREQ, KN or WN or J7NSFREQ
9	POPULATION, PERCAPITA, DL or HPFARE, KN or WN or J7FARE, DL or HPNSFREQ, KN or WN or J7NSFREQ

However, in cases when there is too little cross-section or time-series data to obtain very precise coefficient estimates, a pooled estimation may have to be performed. One way to control for time-varying cross-section coefficients is to include dummy variables for each time unit -- for each quarter in a time series, for example. In this case, the value of each dummy is the differential amount by which the coefficients for the quarter under examination are different from the coefficients for the base year. However, if the data are drawn from a short enough period of time, it may be acceptable to disregard time-varying dummies.

In a 1982 study of air travel demand, for example, Abrahams pooled data from 80 of the largest 100 U.S. O&D city-pairs over 20 consecutive quarters.[42] He further aggregated the data into seven groups according to distance, geographical location and percent vacation traffic. To correct for unexplainable cross-section differences, he added

[42] Michael Abrahams, "A Service Quality Model of Air Travel Demand: An Empirical Study," *Transportation Research-A* Vol. 17A, No. 5 1983: 385-393.

dummy variables for each city-pair. However, he did not do so for each quarter in the time series. Apparently, he was more concerned with the possible aggregation bias from pooling different city-pair data than with model bias from pooling a combination of cross-section and time-series data.

In this thesis, the demand models developed for each local hub market scenario do not include dummies that vary either by cross-section or over time. There are no cross-section dummies because the explanatory variables considered in the models should explain most of the difference between city-pairs. Also, cross-section dummies would probably be correlated with the variables that vary between city-pairs, lessening the precision of those coefficient estimates. There are no time-series dummies because the time period from which the data comes -- second quarter 1993 through second quarter 1995 -- is relatively short. It is unlikely that the explanatory variable coefficients would vary much in that amount of time. Given the above reasons, and the reality that adding dummy variables would reduce the degrees of freedom in three relatively small samples (the competitive scenarios),[43] it was decided that the addition of dummies to the demand models would unnecessarily complicate the process of specifying the regressions and interpreting their results.

4.2.1.3 Serial Correlation

Another factor that needs to be considered when using time series data is serial correlation. According to Pindyck and Rubinfeld, "Serial correlation occurs in time-series studies when the errors associated with observations in a given time period carry over into future time periods."[44] Serial correlation is very common in time series data because many variables tend to grow or decline over time without much fluctuation. At the same time, serial correlation violates one of the major assumptions upon which regression estimation of coefficients is based. That is, the use of regression to estimate coefficients assumes that

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[43] Degrees of freedom are calculated as the number of observations minus the number of parameters to be estimated. As the number of degrees of freedom decreases, parameter estimates become less precise.

[44] Robert Pindyck and Daniel Rubinfeld, *Econometric Models and Economic Forecasts* (New York: McGraw-Hill, Inc., 1991) 137.

observational errors are randomly distributed around the regression "line." This is clearly not true if the errors are serially correlated.

The presence of serial correlation in a regression implies that the coefficient estimates are not as precise as they otherwise would be. Fortunately, serial correlation is relatively easy to correct using a procedure known as "generalized differencing." Once generalized differencing is performed, the statistical significance of the calculated correlation coefficient between successive errors can be tested. In this thesis, this correlation coefficient is calculated for every demand model. If it is significant at a 5% level, then the coefficient estimates from the generalized differencing regression are reported. Otherwise, the coefficient estimates from the non-differenced regression are reported because no serial correlation can be assumed.

4.2.1.4 Simultaneity

Many real-world processes are better modeled by a set of simultaneous and interdependent equations than by a single equation with one dependent variable and one or more explanatory variables. The main rule for determining whether a process needs to be modeled as more than one equation is if one or more of the explanatory variables are clearly affected by either the dependent variable or by one or more of the other explanatory variables. This occurs, for example, in traditional demand-supply models because the price of a product is simultaneously determined by the interaction of producers and consumers in a market.[45] If simultaneity is present, then estimation using traditional single-equation regression techniques will not produce reliable estimates for the explanatory variable coefficients.

In air travel demand modeling, simultaneity may arise between airline passengers and many of the transport supply variables. For example, an increase in the number of flights in a market will clearly stimulate demand. But it seems equally true that the number of flights is partly a result of the number of potential passengers in the market in the first

[45] Pindyck and Rubinfeld, 288.

place. This implies that an airline market demand model should be estimated using simultaneous-equation techniques. However, the literature does make a distinction between demand on a route with mostly local traffic versus demand on a route with substantial connecting or 1-stop traffic.[46] In the latter case, transport supply variables such as the number of flights are believed to depend more on the number of passengers transiting the route as part of their 1-or more stop O&D itinerary than on the number of passengers in the local market. The question is how much through or connecting traffic must exist to obviate simultaneous-equation estimation? Obviously, a traditional carrier's local hub market demand seems exempt, but it is unclear whether low-cost airlines, many of whom carry as much as 35% non-local traffic also qualify. The demand models estimated in this thesis assume that they do. Every airline and market demand model is estimated using traditional single-equation regression techniques.

4.2.1.5 Seasonality

Seasonality can also be a problem in time-series regression. For example, it is widely known in the air travel industry that air carrier load factors are highest in the summer, because this is when the majority of Americans take their yearly vacations. However, it is very difficult to isolate the effects of non-cyclical explanatory variables such as those used in this thesis when there has been no account made for the seasonality of demand. If the number of passengers increases in a market between the second and third quarter of the year, while one or more of the airlines simultaneously increase flight frequency, how much of the demand increase is attributable to seasonality and how much is attributable to an increase in the number of flight options?

To control for seasonality, all the passenger data in this thesis was deseasonalized before use in the demand models. The deseasonalization process is fairly straightforward and involves the calculation of quarterly seasonal indices by market based on three years

[46] Ghobrial and Kanafani, 137.

of market[47] passenger numbers.[48] For each year, the seasonal index is derived by dividing the quarterly passenger figure by the mean quarterly passengers. The final seasonal indices are straight averages of the individual quarterly seasonal indices. All passenger data was deseasonalized by dividing actual quarterly passengers by the quarterly seasonal indices.

4.2.2 Reporting Model Results

For each demand model, the three most important regression results are reported (Table 4.3). These include the coefficient estimates, the P-value for each coefficient estimate, and the adjusted R^2 for the entire regression. As discussed in Section 4.1, the coefficient estimates in a multiplicative demand model are the elasticities of the explanatory variables with respect to the particular measure of demand -- in this case, two-way quarterly O&D air carrier or market passengers. Elasticity estimates are important because they show the sensitivity of demand to the same proportional changes in each of the explanatory variables. Thus, they avoid the problems of comparing the effects of variables measured in different units. For example, it is difficult to compare the absolute effects of a one unit increase in quarterly flight frequency with a $1 increase in the average fare. Although the price increase may have the larger absolute effect on demand, the comparisons are not really "fair" because the fare increase may represent a much greater proportion of the initial fare. Elasticities are one way to control for such effects.

[47] Seasonal indices were not developed for each carrier in the market. Instead, seasonal indices were created using total market passenger numbers and then applied to traditional and low-cost carrier, and market passenger numbers.

[48] For a full explanation of seasonal adjustment, please see Pindyck and Rubinfeld, 432-434.

Table 4.3: Description of Reported Demand Model Statistics

Statistic	Description
Elasticity	Measures sensitivity of passenger numbers to small changes in explanatory variables. Specifically, the % change in passengers for a 1% change in the value of the explanatory variable.
P-Value	The probability that, despite a non-zero elasticity estimate, the "true" elasticity is actually equal to zero. The higher the P-Value, the less likely that changes in, say, flight frequency have any real effect on the number of passengers.
Adjusted R^2	Measures the amount of variance in passengers "explained" by the combined variance of all the explanatory variables. A model with a high adjusted R^2 "fits" the data well.

The P-value is simply the probability that a coefficient estimate is not statistically different from zero. In other words, the P-value is the probability that an explanatory variable has no effect on the dependent variable. As the P-value increases, the greater the likelihood that a coefficient estimate is actually zero despite the non-zero value of the estimate. In most empirical work, a coefficient estimate with a P-value of .05 or less is interpreted as statistically significant because there is less than a 5% chance that the coefficient is actually zero. However, in some studies P-values as high as .1 and as low as .01 are also used as cutoffs for statistical significance. In this thesis, a coefficient with a P-value of .05 or less is interpreted as statistically significant.

The adjusted R^2, also known as $\overline{R}^2$ or "R-bar squared," is a measure of how well a model's explanatory variables "fit" the data. Specifically, the adjusted R^2 measures the proportion of variance in the dependent variable "explained" by variance in the explanatory variables.[49] In general, a model with more statistically significant explanatory

[49] For a detailed description of adjusted R^2, please see Pindyck and Rubinfield, 77-79 or Damodar Gujarati, *Basic Econometrics* (New York: McGraw-Hill, Inc., 1995) 207-209.

variables will also have a higher adjusted R^2 because a greater proportion of the causes of variance in the dependent variable will be a result of variance in the explanatory variables. A model with many statistically significant explanatory variables and a high adjusted R^2 is considered to be a "good model."

Although it is tempting to search for that combination of explanatory variables that maximizes the amount of explained variance in the dependent variable, it must be realized that the most important information in any regression is the direction, magnitude and statistical significance of the explanatory variable coefficients. Indeed, a model that explains much of the variance in the dependent variable but has many statistically insignificant coefficient estimates is very suspicious because it means that a large proportion of the explained variance is due to random chance. Thus, very few conclusions can be drawn from the model. In this thesis, the demand model results report the adjusted R^2 along with the elasticity estimates and P-values to give some sense of how well the explanatory variables -- population, per capita income, average fare, nonstop frequencies and flight time -- fit the dependent variable -- passengers. However, the adjusted R^2 is meant to be viewed in the context of the elasticity estimates and P-values; clearly, it is the least important of the three reported statistics.

The traditional carrier, low-cost carrier and market demand models will be compared both within and between competitive scenarios using the above tools -- the elasticity estimates, P-values and adjusted R^2 -- and tables of descriptive summary statistics. These tables list, for each competitive scenario, the mean, standard deviation, maximum and minimum for each of the explanatory variables for each carrier and for the market. Descriptive statistics aid in the interpretation of elasticity estimates and elasticity differentials because they illustrate the ranges of absolute values for which the elasticities are calculated. Hopefully, when the elasticity estimates and explanatory variable values are synthesized using the airline choice relationships described in Chapter 3, a more complete story of traditional versus low-cost carrier competition will emerge.

4.2.3 Expectations

In general, one expects increases in population, per capita income and flight frequency to increase the number of airline and market passengers. Also, because a seat on one airline is a substitute for a seat on another airline, one expects an increase in one airline's fares to increase the number of passengers on the other airline. So the population, per capita income, own-frequency and cross-fare elasticites of demand should all be positive. By contrast, increases in own-fare and flight time should decrease the number of airline and market passengers. Also, an increase in the number of flights by one airline should decrease the number of passengers on the other airline. So the own-fare, flight time and cross-frequency elasticities of demand should all be negative.

A review of elasticity estimates from the literature suggests the range of values that each elasticity might take. It should be noted that these estimates are for the O&D market, and not for any specific airline.

Population. A 1972 study of 100 short-haul (500 miles or less) city-pair markets by Verleger found a statistically significant (at the 5% level) population proxy elasticity estimate of .54. For city-pair markets between 500 and 1000 miles apart, Verleger found a statistically significant elasticity estimate of .47. However, Verleger used the number of telephone calls between the two cities, rather than the product of their populations.[50]

Per Capita Income. The same Verleger study found statistically significant elasticity estimates for per capita income of .12 for markets under 500 miles apart and .18 for markets separated by between 500 and 1000 miles.[51]

Own-Fare. Verleger estimated market price elasticity at -1.03 for markets under 500 miles apart and -.91 for markets between 500 and 1000 miles. However, only the short-

[50] P.K. Verleger, "Models of the Demand for Air Transportation," *Bell Journal of Economics Management Science* Vol. 3 No.2 1972.

[51] Verleger, 1972.

haul estimate was statistically significant.[52] In 1974, DeVany estimated market price elasticity at -1.02 for a 400-mile trip and -1.07 for a 650-mile trip.[53] In 1981, Ippolito calculated much less elastic price-elasticites at -.525 for a 440-mile trip and -1 for an 830-mile trip.[54]

Own Flight Frequency. In their 1984 study of short- and medium-haul monopoly city-pair markets, Talley and Eckroade found statistically significant market frequency elasticity of demand estimates that ranged from .97 to 1.55.[55]

Flight Time. Ghobrial and Kanafani's 1995 study of demand in the 100 largest U.S. city-pair markets found a statistically significant flight time elasticity estimate of -.511. However, the estimate is found without controlling for market distance.[56]

Because econometric studies of individual airline demand are difficult to find, actual cross-fare and cross-frequency elasticity of demand estimates for individual airlines from previous works are not reported here. However, the literature is replete with cross-elasticity estimates for other goods which, like seats on two different airlines, are relative substitutes. In one study, for example, the cross-price elasticity of demand for chicken with respect to beef, pork and fish was found to be .23, .16 and .004 respectively.[57] While cross-price elasticities greater than zero indicate at least some degree of substitutability, it is generally agreed that two goods are extremely good substitutes if their cross-price elasticities approach 1. In fact, in statistical studies, it is unusual to find cross-price

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[52] Verleger, 1972.

[53] A.S. DeVany, "The Revealed Value of Time in Air Travel," *Review of Economics and Statistics* Vol. 56 February 1974: 77-82.

[54] R.A. Ippolito, "Estimating Airline Demand with Quality of Service Variables," *Journal of Transport Economics and Policy* Vol. 15 January 1981: 7-15.

[55] Talley and Eckroade, 1984.

[56] Ghobrial and Kanafani, 1995.

[57] George Brandow, "Interrelations Among Demands for Farm Products and Implications for Control of Market Supply," *Pennsylvania Agricultural Experiment Station Bulletin 680* 1961.

elasticities greater than 1.[58] Presumably, if it were tested, the same results would hold for cross-frequency elasticities as well.

The direction and magnitude of the elasticities estimated in the local hub market demand models should be similar to those based on the literature, especially for markets as a whole. Individual airline elasticities should be more variable than market elasticites due to their higher level of disaggregation. For example, one would expect a market price-elasticity of demand to be more or less an average of the price-elasticites of demand for the individual airlines. Thus, the actual airline elasticities should fluctuate around the market elasticity. In general, the range of the magnitude of the population and per capita income elasticities should be less than or equal to 1, the own-fare elasticities should be between -2 and 0, the own-frequency elasticities should be between 0 and 1, the flight time elasticities should be between -1 and 0, the cross-fare elasticites should be between 0 and 1, and the cross-frequency elasticites should be between -1 and 0 (Table 4.4).

It is more difficult to quantify *a priori* expectations about the absolute difference in elasticity of demand magnitudes between traditional and low-cost carriers. However, consideration of the different market segments for which each type of carrier competes, and the general advantages and disadvantages of each carrier type as discussed in Chapter 3 do allow some relative predictions for all scenarios (Table 4.4):

Population. Because one would expect increases in population to affect all carriers equally, there should be no statistically significant difference in population elasticity estimates between the traditional and low-cost carrier for any competitive scenario.

Per Capita Income. The positive correlation between per capita income and passengers should be stronger for the traditional than the low-cost carrier because people tend to spend more on "luxury" items when their incomes increase, so they should be more willing

[58] Roy Ruffin, Intermediate Microeconomics (New York: Harper Collins Publishers, 1992) 127.

Table 4.4: A Priori Signs, Magnitudes and Relationships for Demand Model Explanatory Variables

Variable	Elasticity Sign	Elasticity Magnitude (All Carriers & Market)	Elasticity Difference (Traditional versus Low-Cost Carrier)
POPULATION	positive (+)	$0 \leq E_{pop} \leq 1$	$E_{traditional} = E_{low\text{-}cost}$
PER CAPITA INCOME	positive (+)	$0 \leq E_{percap} \leq 1$	$E_{traditional} \geq E_{low\text{-}cost}$
OWN-FARE	negative (-)	$-2 \leq E_{ownfare} \leq 0$	$E_{traditional} \leq E_{low\text{-}cost}$
OWN-FREQUENCY	positive (+)	$0 \leq E_{ownfreq} \leq 1$	$E_{traditional} \geq E_{low\text{-}cost}$
FLIGHT TIME	negative (-)	$-1 \leq E_{flighttime} \leq 0$	$E_{traditional} \leq E_{low\text{-}cost}$
CROSS-FARE	positive (+)	$0 \leq E_{crossfare} \leq 1$	$E_{traditional} \leq E_{low\text{-}cost}$
CROSS-FREQUENCY	negative (-)	$-1 \leq E_{crossfreq} \leq 0$	$E_{traditional} \geq E_{low\text{-}cost}$

to pay higher fares for the "prestige" of flying the traditional carrier. Also, as per capita income increases, people have more money for travel and will take more airline flights. This makes frequent flyer programs relatively more important and gives an advantage to the traditional carrier because of its superior flight benefits.

Own-Fare. The own-fare elasticity for the low-cost carrier should be larger than for the traditional carrier because the low-cost carrier's passenger mix is weighted towards more price-elastic leisure travelers while the traditional carrier's passenger mix is weighted towards business travelers for whom price is often strictly a secondary concern. Also, the traditional carrier has fewer seats available for lower-revenue local traffic and can earn a fare premium for the capacity shortage.

Own-Frequency. Although it depends on the average number of flights for each carrier, the flight frequency elasticity should be more elastic for the traditional carrier because business travelers tend to value additional flights more than non-business travelers.

Flight Time. The low-cost carrier should have the more elastic flight time elasticity because the longer the flight the more unfavorable its lack of perks like meals, frequent-flyer miles and first class seating is looked upon by potential passengers.

Cross-Fare. Although it depends on the fare differential between carriers, the low-cost carrier should have the more elastic cross-fare elasticity because its passengers are more price-sensitive.

Cross-Frequency. Although it depends on the average number of flights for each carrier, the traditional carrier should have the more elastic cross-frequency elasticity because less of the majority of passengers for whom the traditional carrier is preferred will be denied a reservation on the traditional carrier and be forced to take the low-cost carrier.

* * *

The local hub market demand models estimated in this thesis borrow their functional form and explanatory variables primarily from the air travel demand modeling literature. Still, the pooled nature of these models makes it necessary to correct for more complex factors, like combining cross-section and time-series data, serial correlation and seasonality of demand. Expectations for elasticity estimates, P-values and adjusted R^2 values are based on intuition and results from similar modeling efforts in the past. Differential traditional/low-cost airline elasticity estimates are based on intuition and the discussion of local market airline choice in Chapter 3.

5. Competitive Scenarios

In this chapter, local hub market demand models are estimated for the traditional airline, low-cost airline and total market at three traditional airline hub airports: Phoenix, Arizona; Salt Lake City, Utah; and Atlanta, Georgia. For each airline and total market, elasticity of demand estimates, P-values and R^2 values are reported for all explanatory variables for the set of nine demand models. Individual airline and total market elasticity estimates are summarized by the endpoints of their range across the nine demand models. Differential traditional and low-cost airline elasticity ranges are then interpreted for each competitive scenario using individual airline and total market variable descriptive statistics and the discussion of local market airline choice presented in Chapter 3.

5.1 America West versus Southwest at Phoenix, Arizona (PHX)

5.1.1 Background and Descriptive Statistics

The Phoenix scenario features 80 quarterly observations of 11 city-pair markets. Most of these markets, which are listed in Table 5.1, are short-haul, and connect Phoenix with cities and regions in states that border Arizona: California, Nevada and New Mexico. However, America West and Southwest were able to carry more than 90% of the passengers for at least one quarter in two longer distance markets also: Phoenix-Austin and Phoenix-Kansas City. The mean, standard deviation, maximum and minimum distance for these markets, as well as the population and per capita income of the Phoenix spoke cities, are presented in Table 5.2. Notice that all three variables vary significantly across the Phoenix markets. This implies that there should be enough variation in these variables by which to measure changes in America West, Southwest and total Phoenix market demand. (For descriptive explanatory variable statistics by individual Phoenix market, please see Appendix B.)

Table 5.2 also lists descriptive statistics for the transport supply variables (average fare, nonstop frequency and flight time) used in the Phoenix demand models. Looking at these, the most remarkable aspect of competition between America West and Southwest at Phoenix is that despite the number of local nonstop frequencies that can be supported by America West's hub-and-spoke operation there, Southwest dominates the number of nonstop flights to short-haul destinations common to both carriers. This is apparent from Table 5.2, which shows that for the 11 markets studied in which America West and Southwest carry the majority of passengers, the average number of America West nonstop frequencies per market is 5.9 versus 10.9 for Southwest. One interesting question when the traditional carrier has fewer nonstop frequencies than its low-cost competitor is the extent to which other traditional carrier advantages in short-haul markets -- for example, a superior frequent-flyer program, pre-assigned seating, travel agent dominance, first-class cabin and airport clubs -- can continue to attract higher-paying business traffic whose number one concern is usually schedule.[59]

The descriptive statistics in Table 5.2 can be used to calculate summary statistics for the Phoenix markets. Using the airline and market passengers numbers, for example, the market share and frequency shares for America West and Southwest can be calculated. Notice that America West's 35% average market frequency share translates into an average market market share of a little more than 25%. Using a factor of proportionality equal to 1.7, the market share/frequency share relationship detailed in Chapter 3 predicts a market

[59] According to a 1995 Frequent Flyer magazine poll of 8,500 frequent flyers, the most important consideration when selecting a flight is schedule, followed by frequent flyer program, price, nonstop flight and airport location. In-flight service ranked ninth. Pre-assigned seating was not given as a choice.

Table 5.1: List of Markets Used in Phoenix Demand Models (airport codes in parentheses)

Phoenix, Arizona to/from:	
Albuquerque, New Mexico (ABQ)	Austin, Texas (AUS)
Burbank, California (BUR)	El Paso, Texas (ELP)
Kansas City, Missouri (MCI)	Las Vegas, Nevada (LAS)
Los Angeles, California (LAX)	Oakland, California (OAK)
Ontario, California (ONT)	Sacramento, California (SMF)
San Diego, California (SAN)	

share of about 26% for a 35% frequency share. At first glance, it seems the S-curve model fits the Phoenix markets very well. However, a look at the average fares paid on America West and Southwest reveals that America West was able to obtain the market share predicted by the S-curve model despite a 34% higher average fare than Southwest ($68.05 versus $50.94). These numbers imply that America West's mix of passengers was weighted more heavily towards persons on business than Southwest's and that many business passengers willingly paid higher fares to fly America West.[60] In partial answer to the question posed at the beginning of this section, America West's fare premium at Phoenix is a strong indication that the traditional airline's non-frequency attributes can compensate somewhat for a frequency disadvantage.

[60] As mentioned briefly in Chapter 3, traditional airlines almost always match the fares of other traditional and low-cost airlines. However, many traditional airlines also file one-way fares higher than the highest one-way fare offered by the low-cost airline. This does two things. First, it ensures that if a flight attracts enough higher-revenue connecting passengers to limit the number of local passengers, a local passenger pays a fare comparable to the connecting fare he would displace if he were sold a ticket. Second, it prevents the spill of frequent flying local business passengers who might switch permanently to the low-cost airline if denied a seat too many times.

Table 5.2: Descriptive Statistics for Variables Used in Phoenix Demand Models

Phoenix Descriptive Statistics 11 Markets, 80 Observations (All statistics are by market-quarter) Variable	Mean	Standard Deviation	Maximum Value	Minimum Value
HP PASSENGERS	31,971	17,568	86,320	7,094
WN PASSENGERS	94,304	59,374	240,391	20,298
MARKET PASSENGERS	126,275	74,616	316,342	33,840
POPULATION	2,853,442	2,941,196	9,338,446	631,716
PER CAPITA INCOME	$20,505	$3,103	$25,910	$12,981
HP AVERAGE FARE	$68.05	$22.31	$155.50	$47.90
WN AVERAGE FARE	$50.94	$15.76	$97.80	$37.30
MARKET AVERAGE FARE	$55.99	$19.06	$118.26	$40.12
HP DAILY NONSTOP FREQ.*	5.9	2.8	13.0	3.0
WN DAILY NONSTOP FREQ.	10.9	7.2	26.0	1.0
MARKET DAILY NONSTOP FREQ.	16.8	9.6	36.0	4.0
HP FLIGHT TIME (minutes)	86	28	158	54
WN FLIGHT TIME	85	29	160	55
MARKET FLIGHT TIME	85	29	159	55
DISTANCE (miles)	500	262	1043	256
* Each way				

5.1.2 Modeling Results

The nine demand models for each airline and the combined markets in the Phoenix competitive scenario consist of 80 observations (79 if a correction for serial correlation is used) over 11 city-pair markets. The results from the regressions run on these demand models, including elasticity coefficient estimates, P-values and adjusted R^2's are presented in Table 5.3. As a reminder, the dependent variable in all the demand models is the total number of bi-directional O&D market passengers.

An examination of Table 5.3 reveals that most of the elasticity estimates for the Phoenix scenario are significant at the 5% level for the traditional carrier, low-cost carrier and markets as a whole. The main exception to this is where there was a high degree of multicollinearity between two or more of the explanatory variables. Multicollinearity occurs when two or more explanatory variables have a strong linear relationship. Because this makes it difficult to isolate the effects of any affected explanatory variables on the dependent variable, the explanatory variable coefficient estimates will most likely be imprecise and statistically insignificant.

The calculated correlation coefficients between HPFARE and WNFARE; (.96); HPNSFREQ and WNNSFREQ (.80); HPFARE and HPFLTTIME (.89); WNFARE and WNFLTTIME (.94); and MKTFARE and MKTFLTTIME (.94) indicate high degrees of multicollinearity. Where these sets or combinations of these sets of variables appear in the same demand models, their elasticity estimates become very imprecise and may take counterintuitive signs or values. For example, the correlation between WNFARE and WNFLTTIME affects the elasticity estimates for each variable in the sixth Southwest Airlines model. Although the elasticities for both WNFARE and WNFLTTIME have the proper sign, WNFARE is statistically insignificant (P-Value = .2252) and WNFLTTIME is noticeably larger than it is in the models which do not include both variables at the same time (-1.05 vs. -1.21 and -1.43). And in the final Southwest Airlines demand model, the elasticity estimates implausibly suggest that a 1% increase in the number of quarterly America West flights will actual increase the number of Southwest passengers by .52%.

Table 5.3 also shows that after the first four most important determinants of passenger demand -- population, per capita income, average fare and nonstop frequencies -- are included in the Phoenix demand models, additional explanatory variables do not "explain" any more of the variance in the number of passengers. This is apparent from the adjusted R^2 statistic, which reaches a high between .79 and .83 for the fourth set of demand models. Of course, there are not many more explanatory variables tested beyond the first four in the demand models, and multicollinearity is mostly responsible for poor results in later demand models. However, adjusted R^2 values of around .80 do indicate that the models 4 through 9 explain much of the variance in passenger numbers.

5.1.3 Comparison of Elasticity Coefficients

Although comprehensive, the sheer amount of statistical data presented for Phoenix in Table 5.3 can obscure the important elasticity estimate differences between America West and Southwest. To illustrate these differences, Table 5.4 lists the estimated elasticity range for each explanatory variable across the demand models for both carriers and markets as a whole. The listed elasticity ranges include estimates from the models whose results are questionable because of multicollinearity because often one of the highly correlated variables has a sign and magnitude that makes intuitive sense. In this case, it is assumed that the relationship between this variable and the number of passengers is correctly estimated.

Table 5.3: Phoenix Demand Model Results

		America West			Southwest			Market		
Model	Variable(s)	Elasticity	P-Value	R-bar Squared	Elasticity	P-Value	R-bar Squared	Elasticity	P-Value	R-bar Squared
1	FARE	-0.88	0.0001	0.16	-2.15	0	0.67	-1.63	0.0000	0.59
2	FARE	-0.63	0.0005	0.5	-2.05	0	0.7	-1.52	0.0000	0.68
	POPUL	0.51	0		0.21	0.0018		0.29	0.0000	
3	FARE	-1.09	0	0.69	-2.19	0	0.71	-1.76	0.0000	0.72
	POPUL	0.3	0		0.15	0.0446		0.19	0.0031	
	PERCAP	1.82	0		0.53	0.0915		0.93	0.0011	
4	FARE	-0.34	0.0439	0.8	-1.37	0	0.79	-0.85	0.0000	0.83
	POPUL	0.26	0		0.09	0.1457		0.12	0.0209	
	PERCAP	1.33	0		0.72	0.0081		0.88	0.0001	
	NSFREQ	0.69	0		0.34	0		0.52	0.0000	
5	POPUL	0.29	0	0.81	0.09	0.1173	0.81	0.14	0.0059	0.84
	PERCAP	1.64	0		0.92	0.0007		0.99	0.0000	
	NSFREQ	0.46	0.0024		0.26	0.0001		0.38	0.0001	
	FLTTIME	-0.64	0.0054		-1.43	0		-1.06	0.0000	
6	FARE	0.08	0.7737	0.81	-0.46	0.2252	0.81	-0.38	0.1784	0.84
	POPUL	0.29	0		0.09	0.1371		0.13	0.0101	
	PERCAP	1.66	0		0.9	0.001		0.99	0.0000	
	NSFREQ	0.45	0.0069		0.26	0.0001		0.4	0.0000	
	FLTTIME	-0.73	0.0541		-1.05	0.0058		-0.7	0.0408	
7	POPUL	0.3	0	0.69	0.16	0.0257	0.72	0.19	0.0031	0.72
	PERCAP	1.84	0		0.46	0.1382		0.75	0.0072	
	HPFARE	0.03	0.9327		1.11	0.0526		0.78	0.1182	
	WNFARE	-1.16	0.0157		-3.29	0		-2.66	0.0000	
8	POPUL	0.29	0	0.81	0.09	0.1134	0.81	0.15	0.0028	0.83
	PERCAP	1.56	0		0.58	0.0804		0.74	0.0094	
	HPNSFREQ	0.54	0		0.18	0.0208		0.38	0.0184	
	WNNSFREQ	-0.06	0.7184		0.32	0.086		0.1	0.1250	
	FLTTIME	-0.69	0.0882		-1.21	0		-1.05	0.0000	
9	POPUL	0.26	0	0.8	0.1	0.0835	0.83	0.13	0.0062	0.84
	PERCAP	1.27	0		0.18	0.527		0.4	0.1041	
	HPFARE	-0.12	0.7649		0.99	0.0284		0.66	0.0847	
	WNFARE	-0.3	0.5082		-2.13	0		-1.59	0.0003	
	HPNSFREQ	0.74	0		0.52	0.0016		0.57	0.0001	
	WNNSFREQ	-0.05	0.4605		0.17	0.0292		0.11	0.1019	

One interesting feature of the elasticity estimate ranges in Table 5.4 is that there is not one explanatory variable for which America West's elasticities overlap with Southwest's elasticities. This implies that the two airlines are really serving different markets because the number of each airline's passengers respond so differently to changes in the same socioeconomic and transport supply conditions. Another feature of the elasticity ranges is that, as one would expect, the market numbers are in between the numbers for the two airlines. However, in many cases -- for example, population and per capita income -- the numbers are weighted towards Southwest which is by far the larger local hub market airline.

Table 5.4: Elasticity Ranges for Phoenix Demand Models

Explanatory Variable	America West Airlines Passengers	Southwest Airlines Passengers	Total Market Passengers
Spoke City Population	.26 to .51	.09 to .21	.12 to .29
Spoke City Per Capita Income	1.27 to 1.84	.18 to .92	.40 to .92
Average Fare	-.34 to -1.09	-1.37 to -3.29	-.85 to -1.76
Quarterly Nonstop Frequencies	.45 to .74	.17 to .34	.38 to .52
Scheduled Flight Time	-.64 to -.73	-1.05 to -1.43	-.7 to -1.06
Average Cross-Fare	-.3 to -1.16	.99 to 1.11	N/A
Quarterly Nonstop Cross-Frequencies	-.05 to -.06	.18 to .52	N/A

Although the general differences between the elasticity estimate ranges for America West, Southwest and the total market are notable, the main purpose of calculating elasticity estimates for the competitive scenarios is to compare the ranges across the airlines for each explanatory variable individually. This way, the differences in statistical findings can be stated and reasons for the differences proposed. Interpretation of individual elasticity differences can also benefit from examination of airline and market descriptive summary statistics in Table 5.2.

- **Population.** The values for the population elasticity range are much higher (.26 to .51 versus .09 to .21) for the traditional airline, America West, than the low-cost competitor, Southwest. This means that variations in spoke city population have a much greater effect on the number of America West passengers. While increases in population do increase the number of Southwest passengers, the effect is not nearly as strong. Possible reasons for the population elasticity differential include:

1. There seems to be a much closer link between city size and the number of flights connecting that city to America West's Phoenix hub (because larger spoke cities can support more flights beyond the hub as well) than city size and the number of Southwest Phoenix flights, where the demand is often stimulated by fares so low that only a minimum spoke city population base is required.

2. Although Southwest tends to offer more nonstops in larger Phoenix markets, it tends to compensate by offering more 1-stops in smaller markets. For example, according to the June, 1995 O.A.G., Southwest offered 4 daily nonstops between Phoenix and Oakland, but 15 daily 1-stops. And Southwest served Phoenix-Sacramento with 3 daily nonstops, but 4 daily 1-stops.[61] Thus, in many cases, Southwest offers more total effective frequencies in Phoenix short-haul markets than implied by the nonstop frequency variable in the demand models. Although Southwest still flies more traffic between Phoenix and larger cities, because the number of total flight offerings in the smaller markets is far beyond what the markets in some sense "deserve", so much traffic is stimulated that some of the effect of the population differential between different-sized Phoenix markets is obscured.

[61] Official Airline Guide, North American Edition, June, 1995.

- **Per Capita Income.** The values for the per capita income elasticity range are much higher for America West (1.27 to 1.84) than for Southwest (.18 to .92). This implies that variation in per capita income between and within markets has a larger effect on the number of America West passengers. For Southwest, higher per capita income in the markets it serves are also correlated with increased numbers of passengers, but not to the same extent. Possible reasons for the per capita income elasticity differential include:

1. Higher per capita incomes are associated with more business activity at a location. Increased business activity is associated with more employee airline travel. As the level of employee airline travel increases, so does the importance of real and perceived on-ground and in-flight services, particularly frequent flyer programs and the number of destinations served nonstop from the business location. Because the benefits of its frequent flyer program are superior to Southwest and because it offers flights to more nonstop destinations from Phoenix than Southwest,[62] America West receives a disproportionate amount of increases in employee airline travel.

2. According to economic theory, as people's per capita income increases, so will their level of expenditures. However, the amount spent on two different items will not necessarily increase proportionately. The item for which expenditures do not increase proportionately with income is called a "necessity" because the fraction of expenditures devoted to it declines as income increases. By contrast, the item for which expenditures increase disproportionately with income is a "luxury." In this context, when people have more money to spend on airline travel, they may opt for the increased comfort or "prestige" of the traditional carrier (America West) over the no-frills service quality or "vulgarity" of the low-cost carrier (Southwest). This may also help explain why America West can sustain a fare premium at Phoenix despite its severe frequency disadvantage relative to Southwest.

[62] According to Phoenix Sky Harbor International Airport and Southwest Airlines, America West (including its commuter partner Mesa Airlines operating as America West Express) served an average 55 cities nonstop from Phoenix compared to 23 for Southwest in the second quarter of 1995.

• **Average Fare.** The values for the average fare elasticity range are much larger for Southwest (-1.37 to -3.29) than for America West (-.34 to -1.09). This implies that the same proportional decrease in either airline's average market fare has a larger proportional effect on the number of Southwest passengers than the number of America West passengers. Possible reasons for the average fare elasticity differential include:

1. America West has a better frequent flyer program and flies nonstop to more destinations from Phoenix than Southwest. Also, it offers services like pre-assigned seating, in-flight meals and movies, and airport clubs which Southwest does not offer at all. And despite its frequency disadvantage, America West generally offers enough frequencies to and from Phoenix to remain a viable choice for travelers with high values of time. Because relatively price-insensitive frequent business travelers are more likely to value these attributes when choosing an airline, some will choose America West regardless of the fare it charges and many more will pay up to a certain amount more to fly America West.

By contrast, Southwest attracts a disproportionate number of passengers based on low fares alone. These passengers are price-elastic; small changes in fare should have a large effect on the number wanting to fly. Although some business travelers are undoubtedly attracted to Southwest's service consistency and higher number of frequencies, their numbers are dwarfed by the amount of passengers traveling on vacation or visiting friends and relatives. So the Southwest average fare elasticity estimates are very negative and very large.

2. Because America West carries far more higher-revenue connecting traffic than Southwest on its Phoenix flights, it has less capacity for local passengers on higher demand days. Economics teaches that to maximize profits, one should raise prices in times of shortage.[63] This is exactly what America West does, charging higher fares to any

[63] Imagine if America West did not charge higher fares for its scarce capacity. Then, its revenues would decrease because it would still fill all its seats, but at a significantly lower average fare.

local passenger that might displace a connecting booking request. By virtue of their greater willingness to pay higher fares on higher demand days, America West's passengers are more price-inelastic than passengers who fly Southwest.

- **Nonstop Frequency.** The values for nonstop frequency elasticity are much larger for America West (.45 to .74) than for Southwest (.17 to .34). This implies that the same proportional increase in either airline's number of nonstop frequencies has a larger proportional effect on the number of America West passengers, although the frequency elasticities for Southwest are also positive and largely significant (see Table 5.3). Possible reasons for the frequency elasticity differential include:

1. According to Table 5.2, America West had an average 5.9 daily nonstop frequencies to and from Phoenix while Southwest had 10.9. At those numbers, an additional flight by America West creates disproportionately more roundtrip opportunities than an additional Southwest flight. The diminishing returns from increases in frequency share above 50% are apparent from the theoretical market share/frequency share formula presented in Chapter 3. Recall that with a proportionality factor of 1.7, this formula was:

$$MS_i = \frac{FS_i^{1.7}}{\sum_j FS_j^{1.7}} \tag{5.1}$$

Assuming all the Phoenix markets are at saturation frequency, an increase in America West frequency share from 6/17, or 35% to 7/18, or 39% should increase America West market share by 23%, from 26% to 32%. However, an increase in Southwest frequency share from 11/17, or 65% to 12/18, or 67% should only increase Southwest market share by 3.3%, from 74% to about 76.5%. In other words, because America West has so many fewer frequencies than Southwest in the average Phoenix market, increases in America West frequencies should have a larger proportional impact on America West's number of round-trip opportunities.

2. America West's ability to maintain an average Phoenix market share equal to that predicted by the market share/frequency share relationship and earn a significant fare premium for its passengers implies that the average Phoenix passenger prefers to fly America West over Southwest, all else equal. More potential passengers may call America West first for a local Phoenix flight. However, America West's higher volume of connecting traffic means that it often charges higher fares than Southwest. When this happens, many price-elastic passengers choose to fly Southwest instead. An additional America West flight should reduce this spill because more seats will be available at Southwest-level fares.

3. In many competitive short-haul markets, an airline must offer a sufficient number of frequencies to capture more lucrative business travelers. Although many Phoenix-based business travelers are probably cemented to America West through its frequent flyer program and greater number of nonstop destinations, America West's frequency disadvantage must cost it business passengers who originate at spoke cities, where Southwest may have relatively more flights and where America West's frequent flyer program should not have the same advantage as in Phoenix.[64] In this context, additional America West flights should take away some of the mostly spoke-originating business traffic currently flying Southwest. Additional Southwest flights, by contrast, mostly just confirm to business travelers who already fly Southwest that it has the most flights.

Flight Time. Flight time elasticity values are larger for Southwest (-1.05 to -1.43) than America West (-.64 to -.73). Thus, the same proportional increase in Phoenix market flight time has a larger proportional decrease on the number of Southwest passengers. Significantly, this means that as flight time (or, equivalently, market distance) increases, America West's market share improves relative to Southwest, <u>independent of any nonstop frequency share differential</u>. This is illustrated in Figure 5.1, which regresses America

[64] For example, Southwest offered 75 weekday flights from San Diego to various destinations in June, 1995, while America West offered only 9. Thus, although America West's proportion of short-haul Phoenix flights relative to Southwest was low, its proportion of San Diego flights relative to Southwest was even lower. (Source: Southwest Airlines June, 1995 flight schedule and the June, 1995 O.A.G. North American Edition.)

West and Southwest market share on each airline's nonstop flight time from Phoenix. Although the regression lines in Figure 5.1 do overestimate the market share/flight time relationship somewhat (because Southwest flies relatively fewer nonstop flights as market distance increases), there is clearly a positive relationship between longer flights and America West market share versus Southwest. Why might the flight time elasticity differential exist?[65] Possible reasons include:

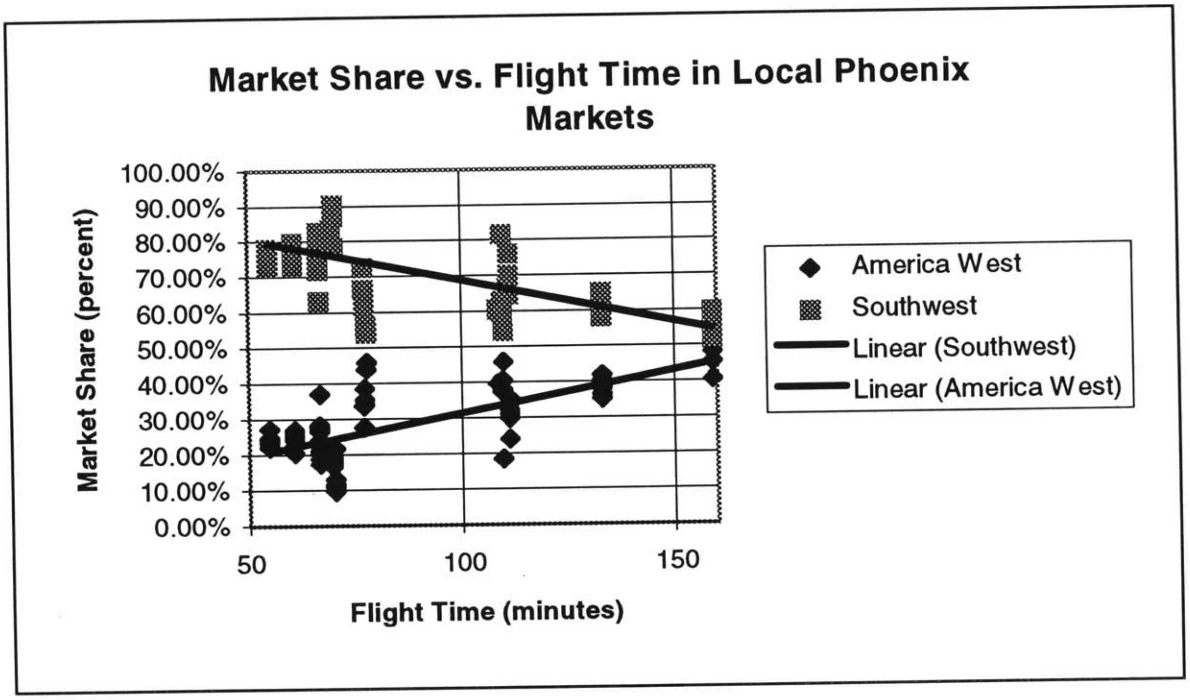

Figure 5.1: Market Share versus Flight Time in Local Phoenix Markets

1. Passengers are less willing to fly Southwest on longer flights because as flight time increases so does the importance of service attributes like frequent flyer miles, pre-assigned seating and in-flight food and beverage service.

[65] Note that, as one would expect, the number of passengers flying either carrier decreases with additional flight time (or distance), all else equal. Markets that are farther apart should have less airline traffic because of the additional trip cost in time and money.

2. Travel agents are biased towards selling America West tickets on longer flights, because as market distance increases, so does the absolute fare differential between an average America West and Southwest ticket (see Figure 5.2).

- **Cross-Fare.** As explained in Chapter 4, the cross-fare elasticity is defined as the percentage change in one airline's passengers in response to a 1% change in the other airline's fares. The values for cross-fare elasticity make sense for Southwest passengers (.99 to 1.11) but do not make sense for America West passengers (-.3 to -1.16). The Southwest demand models' cross-fare elasticities indicate that a 1% increase in America West fares will increase the number of Southwest passengers by about 1%. Because higher fares by either airline decrease the number of total passengers, it must be assumed that the increase in Southwest passengers comes entirely at the expense of America West. Most importantly, the approximately unit-elastic cross-fare elasticity implies that America West and Southwest are very good price substitutes. This is what one would expect for the majority of local Phoenix market passengers.

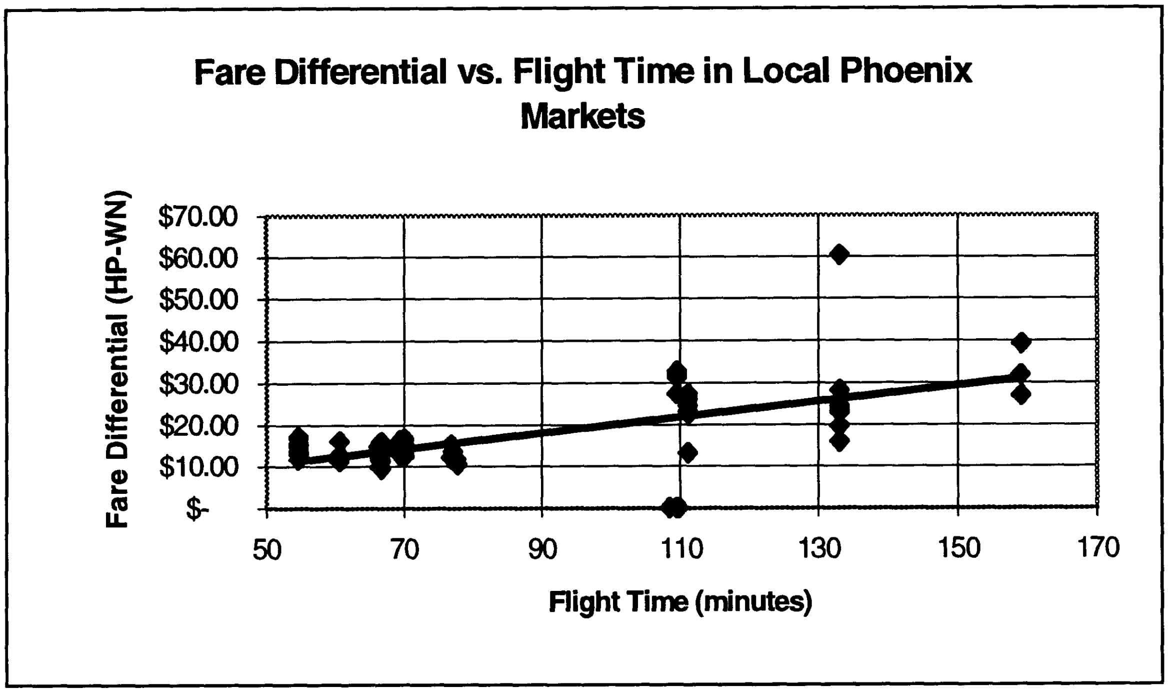

Figure 5.2: Fare Differential (America West minus Southwest) versus Flight Time in Local Phoenix Markets

The America West demand models' cross-fare elasticities indicate that a 1% increase in Southwest fares actually decreases the number of America West passengers by .3% to 1.16%. This counterintuitive result is most likely caused by multicollinearity and/or the aggregate nature of the data. However, it is possible that many passengers in local Phoenix markets are only stimulated to fly by Southwest's fares. If those fares increase, and America West matches the fare increases (as one would expect), then a lot of potential passengers no longer want to fly. This would cause decreases in both Southwest and America West passengers.

- **Cross-Frequency.** As explained in Chapter 4, the cross-frequency elasticity is the percentage change in one airline's passengers due to a 1% change in the number of other airline frequencies. The values for cross-frequency elasticity make sense for America West passengers (-.05 to -.06) but do not make sense for Southwest passengers (.18 to

.52). However, according to Table 5.3, the cross-frequency elasticities of Southwest flights to America West passengers are not very significant. This seems to imply that an additional Southwest flight has no effect on the number of America West passengers, and is similar to the previously discussed idea that Southwest has so many more flights than America West in the average Phoenix market that additional Southwest flights are hardly perceptible to America West passengers.

Although it is easy to interpret the insignificance of additional Southwest flights on the number of America West passengers, the idea that additional America West flights could actually stimulate Southwest traffic is hard to understand. As with the estimated negative effect of changes in Southwest fare on America West passengers (which might be a proxy for price matching), it is safest to blame multicollinearity and/or model misspecification for the counterintuitive results.

5.2 Delta versus Morris/Southwest at Salt Lake City, Utah (SLC)[66]

5.2.1 Background and Descriptive Statistics

Before any descriptive statistics for the Salt Lake City scenario can be presented, there are two flaws with the Morris Air data that must be discussed.[67] The most serious problem is that the Morris fare data has been "approximated" by Database Products, Inc., the company that compiles the fare data and places it on CDROM for public use. Because Morris Air never filed passenger and fare data with the U.S. Department of Transportation, there was no way to determine the average fare paid in any Morris Air markets. Believing that some data was better than no data, Database Products, Inc. created Morris fare data by multiplying Morris' average system yield by the nonstop mileage between all city-pairs in its route system. The difficulty with this "solution" is that (1) because yield decreases with distance, calculating average fare as system yield

[66] Recall that Morris Air served Salt Lake City unitl the fourth quarter of 1994 when Southwest bought Morris and assumed its SLC routes. Until then, Southwest had no service to SLC.

[67] Note that only Morris Air data is measured incorrectly. There is nothing wrong with the Southwest data, which starts with the fourth quarter of 1994.

multiplied by market distance will underpredict the average fare for shorter flights and overpredict it for longer flights, all else equal; (2) airline fares are subject to competitive pressures so that sometimes there is actually very little relationship between airfares and distance; and (3) airfares are often set over many markets together, so that all markets within a certain distance range have the same set of airfares. These caveats should be kept in mind when drawing conclusions from any Salt Lake City demand models that include Morris/Southwest fare as an explanatory variable.

As alluded to above, Database Products, Inc. was also forced to manipulate Morris passenger data. Apparently, Morris did not report that any of its passengers used more than one ticket coupon to fly within its route system. This implies, erroneously, that not one Morris passenger changed planes at Morris' Salt Lake City "hub" to fly between two Morris cities that did not have direct service. The result is that the data assumes all connecting itineraries (which should be a very small proportion of total Morris itineraries) are actually two separate local nonstop flights to and from Salt Lake City. This means that Morris passenger numbers in local Salt Lake City markets (and thus the Morris demand models) are slightly overestimated. However, the effect of systematic overestimation of the dependent variable on the demand model elasticity estimates is unclear. As with the error in the Morris average fare variable, it is best that the reader simply consider the error in Morris passengers before making any conclusions based on demand model results.

With the errors in Morris average fare and passenger data in mind, the list of 12 Salt Lake City markets is presented in Table 5.5. Many of the Salt Lake City spoke cities -- especially in southern California -- are the same ones used in the Phoenix demand models. In general, however, the Salt Lake City markets are more short-haul than the Phoenix markets, with an average distance of 534 miles (500 miles for Phoenix), a maximum distance of 689 miles (1043 miles for Phoenix) and a standard deviation of 116 miles (262 miles for Phoenix).

Despite the differences in market distance, the most important difference between traditional and low-cost carrier competition at Salt Lake City and Phoenix is that whereas at Phoenix the traditional carrier has far fewer nonstop flights than the low-cost carrier, the reverse is true at Salt Lake City: Delta, the traditional carrier, has many more flights at Salt Lake City than the low-cost carrier, Morris/Southwest.[68] This is apparent from Table 5.6, which shows that for the 12 markets for which Delta and Morris/Southwest carry the majority of passengers, the average number of Delta nonstop frequencies per market is 4.9 versus 2.6 for Morris/Southwest. This compares with an average of only 5.9 nonstop frequencies for America West at Phoenix versus 10.9 for Southwest.

Table 5.5: List of Markets Used in Salt Lake City Demand Models (airport codes in parentheses)

Salt Lake City, Utah to/from	
Boise, Idaho (BOI)	Colorado Springs, Colorado (COS)
Las Vegas, Nevada (LAS)	Los Angeles, California (LAX)
Oakland, California (OAK)	Orange County, California (SNA)
Portland, Oregon (PDX)	Reno, Nevada (RNO)
Sacramento, California (SMF)	San Diego, California (SAN)
Seattle, Washington (SEA)	Spokane, Washington (GEG)

The other major difference between the Salt Lake City and Phoenix scenarios is that Salt Lake City markets are much less densely traveled over very similar average distances and only slightly smaller spoke city populations. According to Table 5.6, the average number of quarterly passengers in Salt Lake City markets is roughly half that for Phoenix (63,711 vs. 126,275) for an average market distance differential of only 34 miles (534 vs. 500) and a spoke city average population differential of about 600,000 people (2,280,128 vs. 2,853,442). Also, the lower density of Salt Lake City markets occurs despite a much higher average quarterly per capita income than Phoenix markets ($23,056

[68] Other hub airports at which the traditional carrier has more frequencies, on average, than the low-cost carrier in common markets include Denver (United vs. Frontier), Newark (Continental vs. KIWI), Baltimore (USAir vs. Southwest) and St. Louis (TWA vs. Southwest).

vs. \$20,505). However, the Phoenix area is over twice as large as the Salt Lake City area, and is more widely perceived as a tourist destination. And, of course, the much larger number of low-cost carrier flights on markets connected to Phoenix must account for at least some of the passenger differential with Salt Lake City.

Table 5.6: Descriptive Statistics for Variables Used in Salt Lake City Demand Models

Salt Lake City Descriptive Statistics
12 Markets, 76 Observations

Variable	Mean	Standard Deviation	Maximum Value	Minimum Value
DLPAX	27,029	18,447	79,215	5,806
KNPAX	36,683	20,795	90,658	8,312
MKTPAX	63,711	35,786	169,873	14,571
POPULATION	2,280,128	2,418,141	9,338,446	284,754
PERCAPITA	\$ 23,056	\$ 2,668	\$ 29,881	\$ 19,717
DLFARE	\$ 82.15	\$ 9.27	\$ 105.50	\$ 63.90
KNFARE	\$ 49.86	\$ 8.98	\$ 72.70	\$ 30.40
MKTFARE	\$ 62.96	\$ 9.04	\$ 76.22	\$ 38.81
DLNSFREQ	4.9	2.0	9.0	3.0
KNNSFREQ	2.6	1.4	8.0	1.0
MKTNSFREQ	7.4	2.4	12.0	4.0
DLFLTTIME	91	15	108	58
KNFLTTIME	91	16	110	55
MKTFLTTIME	91	15	109	57
DISTANCE	534	116	689	291

Table 5.6 can also be used to calculate some summary statistics for the Salt Lake City markets. Using the airline and market passengers numbers, for example, the market share and frequency shares for Delta and Morris/Southwest can be calculated. Notice that

Delta's 66% average market frequency share translates into an average market market share of only 42%. Using a factor of proportionality equal to 1.7, the market share/frequency share relationship detailed in Chapter 3 predicts a market share of almost 76% for a 66% frequency share. However, the average fare paid on Delta is also 65% higher than the average fare paid on Morris/Southwest ($82.15 vs. $49.86). Thus, even though Delta carries many fewer passengers per frequency than Morris/Southwest, it generates a substantially higher revenue from each passenger it does carry. Note that the difference in Delta's revenue between the number of passengers and average fare it actually realized during the study period, and the number of passengers and average fare it would realize if it had 76% of the market (with the same $49.86 average fare as Morris/Southwest) is very similar ($2.22 million actual vs. $2.40 million hypothetical). As with America West in Phoenix, these numbers demonstrate that a low market share does not always translate into low revenues.

5.2.2 Modeling Results

The nine demand models for each airline and the combined markets in the Salt Lake City competitive scenario consist of 76 observations (75 if a correction for serial correlation is used) over 12 city-pair markets. The results from the regressions run on these demand models, including elasticity estimates, P-values and adjusted R^2 values are presented in Table 5.7. As a reminder, the dependent variable in all the demand models is the total number of bi-directional O&D market passengers.

An examination of Table 5.7 reveals that the most consistently significant elasticity estimates for the Salt Lake City scenario are population, nonstop frequency and average fare. Moreover, the direction and magnitude of these elasticities always agrees with *a priori* expectations. Elasticity estimates for per capita income and flight time are mostly insignificant. However, while the direction and magnitude of the estimated per capita income elasticities is correct, the flight time variable takes on positive values for Delta. Possible reasons for this will be discussed in the next section. Finally, although the cross-fare elasticities are generally more significant than the cross-frequency elasticities, the latter more often have the proper sign. Again, possible reasons will be discussed in the next section.

Table 5.7: Salt Lake City Demand Model Results

		Delta			Southwest			Market		
Model	Variable(s)	Elasticity	P-Value	R-bar Squared	Elasticity	P-Value	R-bar Squared	Elasticity	P-Value	R-bar Squared
1	FARE	-1.22	0.0009	0.75	-0.05	0.8836	0.43	-1.05	0.0061	0.61
2	FARE	-0.91	0	0.94	-0.57	0.0671	0.61	-1.31	0	0.86
	POPUL	0.67	0		0.51	0		0.61	0	
3	FARE	-0.96	0	0.94	-0.57	0.0703	0.61	-1.35	0	0.86
	POPUL	0.68	0		0.51	0		0.61	0	
	PERCAP	0.46	0.1328		0.33	0.5583		0.42	0.1605	
4	FARE	-0.97	0	0.94	-0.44	0.0468	0.77	-1.03	0	0.87
	POPUL	0.65	0		0.31	0		0.54	0	
	PERCAP	0.46	0.1347		0.52	0.1084		0.49	0.0384	
	NSFREQ	0.25	0.0184		0.67	0		0.33	0.0002	
5	POPUL	0.56	0	0.92	0.31	0	0.76	0.46	0	0.83
	PERCAP	0.23	0.4557		0.65	0.064		0.41	0.1364	
	NSFREQ	0.36	0.0238		0.67	0		0.54	0.0004	
	FLTTIME	0.6	0.1962		-0.35	0.3146		-0.04	0.9316	
6	FARE	-1.18	0	0.95	-0.43	0.0878	0.77	-1.21	0	0.88
	POPUL	0.4	0		0.31	0		0.42	0	
	PERCAP	0.59	0.0336		0.54	0.1268		0.39	0.0983	
	NSFREQ	0.61	0		0.66	0		0.52	0.0001	
	FLTTIME	1.51	0.0007		-0.05	0.9		0.79	0.0389	
7	POPUL	0.66	0	0.94	0.49	0	0.66	0.55	0	0.84
	PERCAP	0.48	0.1108		0.74	0.1593		0.59	0.0877	
	DLFARE	-0.95	0		-1.4	0.0022		-1.24	0.0001	
	KNFARE	0.3	0.0261		-0.62	0.0364		-0.3	0.0389	
8	POPUL	0.53	0	0.92	0.39	0.0002	0.76	0.48	0	0.87
	PERCAP	0.19	0.545		0.73	0.0436		0.45	0.0658	
	DLNSFREQ	0.35	0.0292		-0.2	0.2939		-0.04	0.7642	
	KNNSFREQ	0.08	0.4174		0.67	0		0.42	0	
	FLTTIME	0.74	0.1444		-0.8	0.1489		-0.45	0.222	
9	POPUL	0.64	0	0.95	0.31	0	0.77	0.43	0	0.87
	PERCAP	0.58	0.0541		0.6	0.082		0.55	0.0258	
	DLFARE	-1.02	0		-0.39	0.2982		-0.62	0.0211	
	KNFARE	0.32	0.0132		-0.48	0.0421		-0.17	0.3185	
	DLNSFREQ	0.31	0.0046		-0.03	0.8315		0.11	0.2528	
	KNNSFREQ	-0.09	0.284		0.64	0		0.35	0	

Compared to Phoenix, the adjusted R^2 values for the Salt Lake City demand models are higher for the traditional carrier (.75 to .95 vs. .16 to .81), lower for the low-cost carrier (.43 to .77 vs. .67 to .83) and higher for the total market (.61 to .88 vs. .59 to .84) In other words, the explanatory variables in the Salt Lake City demand models do a better job of explaining the variance in passengers for Delta and all Salt Lake City markets than the same variables did for America West and all Phoenix markets. But they do a worse job explaining the number of passengers Morris/Southwest carries in Salt Lake City than the amount of passengers that Southwest carries in Phoenix.

The demand model explanatory variables may do a better job explaining Delta's rather than America West's passenger numbers because Morris' frequency disadvantage and lack of name recognition in cities connected to Salt Lake City makes it less of a substitute for Delta passengers than Southwest is for America West passengers. By constrast, many potential passengers flying to and from Phoenix probably use other criteria -- like frequent-flyer program, pre-assigned seating or first class cabin -- when choosing between America West and Southwest; this other criteria is not represented by variables included in the demand models. Why this analysis holds for the traditional carrier and the market, but not the low-cost carrier could well be the result of the previously mentioned "manufacture" of Morris average fare and passenger data.

5.2.3 Comparison of Elasticity Coefficients

As with the complete table of Phoenix demand model results, the large amount of statistical data presented for Salt Lake City in Table 5.7 can obscure the important elasticity estimate differences between Delta and Morris/Southwest. To illustrate these differences, Table 5.8 lists the estimated elasticity range for each explanatory variable across the demand models for both carriers and for the market as a whole. Unlike the Phoenix scenario, multicollinearity is not a serious problem for the Salt Lake City demand models. For example, the calculated correlation coefficients between DLFARE and KNFARE (.03); DLFARE and DLFLTTIME (.16); KNFARE and KNFLTTIME (.65);

and DLNSFREQ and KNNSFREQ (.58) are all much lower than their Phoenix scenario counterparts. However, it is interesting that the correlation between KNFARE and KNFLTTIME is so low, given the distance-based formula used to manufacture Morris average fare data.

Table 5.8: Elasticity Ranges for Salt Lake City Demand Models

Explanatory Variable	Delta Air Lines Passengers	Morris Air/Southwest Airlines Passengers	Total Market Passengers
Spoke City Population	.40 to .68	.31 to .51	.42 to .61
Spoke City Per Capita Income	.19 to .59	.33 to .74	.39 to .59
Average Fare	-.91 to -1.22	-.05 to -.62	-1.03 to -1.35
Quarterly Nonstop Frequencies	.25 to .61	.64 to .67	.33 to .54
Scheduled Flight Time	.60 to 1.51	-.05 to -.80	-.45 to .79
Average Cross-Fare	.30 to .32	-.39 to -1.4	N/A
Quarterly Nonstop Cross-Frequencies	-.09 to .08	-.03 to -.2	N/A

The most notable difference between the elasticity estimates for Delta and Morris/Southwest at Salt Lake City and the elasticity estimates for America West and Southwest at Phoenix is that the differential magnitude of many of the elasticities seems reversed at Salt Lake City. Those explanatory variables for which changes should affect traditional carrier passengers relatively more (per capita income, nonstop frequency) affect them relatively less while the explanatory variables for which changes should have less effect on the traditional carrier (average fare) affect traditional carrier passengers relatively more. Although these differences do not make immediate intuitive sense, an explanation for their appearance will be offered when individual variable ranges are discussed later in the section.

In common with the Phoenix scenario, the ranges for the estimated total Salt Lake City market elasticities are a weighted average of the traditional and low-cost airline elasticities. This simply reflects the dominance of traditional and low-cost carrier flights in markets for which the two carriers have more than 90% combined market share. However, unlike the Phoenix scenario, it is not clear that the market elasticities are weighted towards either the traditional or low-cost carrier (recall that they were weighted towards Southwest's elasticities at Phoenix). This is probably because the frequency shares for Delta and Morris/Southwest are more equal than those for America West and Southwest at Phoenix.

Using the same reporting procedure as the Phoenix scenario, the estimated elasticity ranges for individual explanatory variables for Delta and Morris/Southwest at Salt Lake City are presented below and their differences interpreted using the descriptive statistics from Table 5.6 and the discussion of local market airline choice in Chapter 3.

- **Population.** The values for the population elasticity range are higher (.40 to .68) for the traditional airline, Delta, than for the low-cost competitor, Morris/Southwest (.31 to .51). This means that variations in spoke city population have a greater effect on the number of Delta passengers. While Morris/Southwest does tend to have more passengers in Salt Lake City markets with bigger spoke city populations, the effect is not as strong. Possible reasons for the population elasticity differential include:

1. There seems to be a much closer link between city size and the number of flights connecting that city to Delta's Salt Lake City hub (because larger spoke cities can support more flights beyond the hub as well), all else equal, than spoke city size and the number of Morris/Southwest Salt Lake City flights, where the number of flights in each market seems more dependent on ensuring a common number of nonstops from Salt Lake City to a variety of destinations (see Appendix C).

2. With a weak link between the number of Morris/Southwest flights in a market and that market's combined population, variables like airfare would seem to explain a greater amount of the variation in Morris/Southwest passengers. For example, Salt Lake City-Portland and Salt Lake City-San Diego had an average two Morris/Southwest and four Delta flights throughout the study period. Also, both Portland and San Diego are about the same distance from Salt Lake City. However, Morris/Southwest carried an average of about 30,000 passengers per quarter to and from Portland, but over 34,000 to and from San Diego. The difference is that the average fare paid on Morris/Southwest between Salt Lake City and Portland was $54.21 while the average fare paid between Salt Lake City and San Diego was $51.79. It seems clear that the lower average fare paid by San Diego traffic is chiefly responsible for the greater passenger amounts Morris/Southwest realized in the Salt Lake City-San Diego market as compared to Salt Lake City-Portland.

- **Per Capita Income.** The values for the per capita income elasticity range are higher for Morris/Southwest (.33 to .74) than for Delta (.19 to .59). This implies that variation in the per capita income of spoke cities better explains variation in the number of Morris/Southwest passengers than the number of Delta passengers. However, for both airlines the individual per capita income elasticity estimates are usually not significantly different from zero.

Given *a priori* expectations about the relationship between airline choice and per capita income, it seems highly unlikely that potential passengers in cities with higher per capita incomes would choose Morris/Southwest at a higher rate than Delta. The elasticity results seem especially odd because business traffic, which values flight frequency and service quality more than fare, should become a higher proportion of a market's total traffic as the market's combined per capita income increases. Besides problems with Morris/Southwest data and/or demand model misspecification, the differential per capita income elasticity results cannot be explained.

• **Average Fare.** The values for the average fare elasticity range are larger for Delta (-.91 to -1.22) than for Morris/Southwest (-.05 to -.62). This suggests that the same proportional decrease in either airline's average fare results in a larger proportional increase in the number of Delta passengers. This result is counterintuitive because one expects Delta to carry the majority of price-insensitive business travelers in Salt Lake City markets. Indeed, business travelers' preference for Delta seems confirmed by the 65% average fare premium that Delta earns relative to Morris/Southwest.

In an attempt to determine whether errors in the Morris data were affecting the Morris average fare elasticity estimates, several regressions were run on data from the three quarters after Southwest assumed Morris' Salt Lake City routes. Although the Southwest elasticities were higher than those for Morris, they were still far below the Delta price elasticities. Thus, the manufacture of Morris average fare data does not seem to be the cause for the odd elasticity differentials.

One possiblity why Delta's estimated average fare elasticities might be so much higher than those for Morris and Southwest is that Delta's Salt Lake City flights may have had much lower load factors during the study period. Thus, assuming Delta matched Morris/Southwest's lower fares, Delta would have many more seats to offer to newly stimulated demand. Decreases in Morris/Southwest fares, by contrast, would not have as much impact on the number of Morris/Southwest passengers, because Morris/Southwest aircraft would already be relatively full. Another possibility is that Delta's higher average fare elasticities simply reflect that passengers in Salt Lake City and spoke cities overwhelmingly prefer to fly Delta.

• **Nonstop Frequency.** The values for nonstop frequency elasticity are larger for Morris/Southwest (.64 to .67) than for Delta (.25 to .61). This implies that the same proportional increase in quarterly nonstop frequencies will cause a larger proportional increase in the number of Morris/Southwest passengers, although the frequency elasticities for Delta are all positive and statistically significant as well (see Table 5.7). Possible reasons for the frequency elasticity differential include:

1. The ability by Morris/Southwest to increase its passengers through additional flights at a faster rate than Delta must be primarily the result of the S-shape of the market share/frequency share relationship. As Table 5.6 shows, Delta had an average 4.9 daily nonstop frequencies in Salt Lake City markets while Morris/Southwest had only 2.6. Despite any *a priori* preference by potential passengers for Delta, additional Morris/Southwest flights are more perceptible to travelers in the average Salt Lake City market because the number of Morris/Southwest round-trip possibilities increases at a much faster rate with additional Morris/Southwest flights than does the number of Delta round-trip possiblities increase with additional Delta flights. Thus, the change in either airline's relative frequency share (and hence market share) is greater with changes in Morris/Southwest's rather than Delta's frequency.

2. Assuming that Morris/Southwest's lower average fares and relatively few flights allowed it higher load factors than Delta, the number of reservation requests Morris/Southwest refused should also have been higher than Delta. In this context, additional Morris/Southwest, rather than Delta, flights should have a greater impact on reducing own passenger spill. Thus, changes in the number of Morris/Southwest flights would increase or decrease Morris/Southwest passengers disproportionately compared to Delta.

- **Flight Time.** While estimated flight time elasticity values for Morris/Southwest (-.05 to -.80) are somewhat reasonable, they make little sense for Delta (.60 to 1.51). The flight time elasticity values imply that a 1% increase in Salt Lake City market flight time decrease the number of Morris/Southwest passengers by .05 to .80%. Although these numbers seem quite low, (especially because the estimated flight time elasticity range for Southwest at Phoenix is between -1.05 and -1.43) at least they have the right sign. The estimated Delta flight time elasticities, by contrast, imply that Delta flights of increasing lengths will carry more passengers, simply because the flights are longer.

Calculation of the correlation between flight time and population for Delta in Salt Lake City markets provides evidence that substantial multicollinearity between the two variables is primarily responsible for counterintuitive average fare and flight time estimated elasticity ranges. For Delta, the correlation between flight time and population is about .73. The high correlation probably stems from the geographic truth that the smaller Salt Lake City markets like Boise, Colorado Springs, Reno and Spokane are a shorter distance apart than larger Salt Lake City markets like Orange County, San Diego, Seattle and Los Angeles. Thus, even with a spoke city population variable in the Delta demand models, it seems reasonable that a large, positive flight time elasticity could be estimated.

Another possibility is that Delta's more "inelastic" flight time elasticities again reflect the strong preference by Salt Lake City and spoke city passengers for Delta over Morris/Southwest flights. Here, as with America West in Phoenix, this preference appears as a greater desire by passengers to fly the traditional carrier in longer markets.

Flight time and spoke city population have almost exactly the same correlation for Morris/Southwest as they do for Delta. However, unlike Delta, flight time also has a high correlation with average fare for Morris/Southwest (probably due to the distance-based method used to manufacture Morris average fare data). The result seems to be that for Morris/Southwest the flight time and average fare elasticity estimates "split" their mutual negative impact on passenger numbers. This would explain why both the average fare and flight time elasticity estimates for Morris/Southwest seem so unusually low.

- **Cross-Fare.** According to the elasticity estimates from the Delta demand models, changes in the number of Delta passengers move in the same direction as changes in Morris/Southwest average fare. Specifically, a 1% increase in Morris/Southwest average fare will increase Delta passengers by .30 to .32%. This implies that Delta and

Morris/Southwest are reasonable but not strong substitutes because changes in Morris/Southwest average fare have a small but positive effect on Delta demand.

However, according to the Morris/Southwest demand model elasticity estimates, changes in the number of Morris/Southwest passengers move in the opposite direction as changes in Delta's average fare. The Delta cross-fare elasticity is estimated at between -.39 and -1.40. This implies that travel on Delta and Morris/Southwest is actually complementary because an increase in Delta's average fare is actually correlated with a decrease in Morris/Southwest passengers.

Unlike the different cross-fare elasticity signs for America West and Southwest in the Phoenix scenario, which could be explained with reference to passenger mix and price matching, it is difficult to think of a reason why an increase in the low-cost carrier's fares would increase the number of traditional airline passengers but an increase in the traditional airline's fares would decrease the number of low-cost carrier passengers. One possibility is that Delta used more lucrative commission overrides to increase its dominance of Salt Lake City based travel agents during the study period.[69] Such tactics might mean that, even if Delta raised its fares relative to Morris, potential passengers were not told by travel agents about Morris flights, leaving the passenger to choose between flying Delta or not flying at all.

- **Cross-Frequency.** The cross-frequency elasticity of a 1% change in the number of Morris/Southwest flights on the number of Delta passengers is estimated at -.09% to .08%. The cross-frequency elasticity of a 1% change in the number of Delta flights on the number of Morris/Southwest passengers is estimated at -.03% to -.2%. However, no cross-frequency elasticity estimate is statistically significant.

[69] James Hirsch, "Delta's Bonuses to Travel Agents Spur Inquiry on Anticompetitiveness Question," *Wall Street Journal* 11 October 1993: A, 14:5.

Given the negative effect on the number of one airline's passengers by additional flights by the other airline, both ranges of cross-frequency elasticity estimates make sense. Although none of the cross-frequency elaticities are statistically significant, there is a tendency for additional Delta flights to carry more passengers who may have flown Morris/Southwest than vice versa. This is what one would expect if Delta is regarded as preferable to Morris/Southwest before potential passenger consideration of the differential price and service offerings of the two carriers for a particular flight. Interestingly, because the own-Morris/Southwest frequency elasticity is significantly positive but the cross-Morris/Southwest frequency elasticity is not significantly different from zero, one concludes that most if not all traffic stimulated to fly Morris/Southwest through additional flights is traffic that otherwise would not have flown. Given the adequate total nonstop frequencies in the Salt Lake City markets, these new passengers must all be stimulated by Morris/Southwest's lower fares to and from the Salt Lake City area.

5.3 Delta versus Valujet at Atlanta, Georgia (ATL)

5.3.1 Background and Descriptive Statistics

Common Atlanta market competition between Delta and Valujet has several key attributes that distinguish it from traditional/low-cost carrier competition at Phoenix and Salt Lake City. First, because it uses Atlanta as a quasi-hub, low-cost Valujet should carry a higher proportion of connecting passengers than low-cost point-to-point airlines like Southwest. This implies that Valujet is a more direct threat to Delta's hub-and-spoke operation at Atlanta than Southwest is to America West at Phoenix or to Delta at Salt Lake City. However, it also means that Valujet may have fewer seats to offer local Atlanta passengers on high demand days. Second, the density of the average Atlanta market is proportionately greater than the average Phoenix or Salt Lake City market. Aware that more densely traveled markets can usually support more flights regardless of carrier, other low-cost airlines also fly nonstop in many Atlanta markets common to Delta and Valujet.[70] It will be important to consider the impact of these smaller low-cost

[70] Recall that the greater density of Atlanta markets made it necessary to tradeoff the combined traditional/low-cost carrier 90% market share minimum requirement to 80% to obtain more quarterly market

carriers on the descriptive statistics and elasticity estimates presented for Delta and Valujet later in this section.

The list of markets used in and aggregate descriptive statistics for the Atlanta demand models appear in Table 5.9 and Table 5.10. As Table 5.9 illustrates, all the Atlanta markets are within the southeastern United States. In addition, about half the Atlanta markets -- including Fort Lauderdale, Fort Myers, Orlando, Tampa and West Palm Beach -- consist of vacation destinations in Florida.[71] Also, according to Table 5.10, the average, standard deviation, maximum and minimum Atlanta market distances are quite low compared to Phoenix and Salt Lake City markets. For example, the average Atlanta market is 386 miles in length, compared to 500 miles for Phoenix and 534 miles for Salt Lake City.

All else equal, shorter market distances usually correspond with greater market density. This is certainly true for the Atlanta markets. Even with an average spoke city population of only 1.3 million (compared with 2.9 million for Phoenix and 2.3 million for Salt Lake City), the average Atlanta market still supports almost 13 daily nonstops each direction (compared to about 17 for Phoenix and 7 for Salt Lake City). Notice that only about 11 of these nonstop flights are on Delta or Valujet; the rest are on very small low-cost carriers like Kiwi International (KP) and Air South (WV). Since third quarter 1994, for example, both Kiwi International and Air South have offered nonstop service between Atlanta and Tampa.

Passenger numbers also indicate the influence of carriers other than Delta and Valujet. Table 5.10 shows that the combined number of Delta and Valujet passengers in the average Atlanta market (72,965) is about 92% of total market passengers. Although very large in an absolute sense, this percentage is much smaller than for either Phoenix or

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observations. Also note that in at least one market, Atlanta-Memphis, a traditional airline (here, Northwest) also had nonstop flights. However, like the other airline market shares in all Atlanta markets, Northwest's Atlanta-Memphis market share was under 20%.

[71] Atlanta-Jacksonville, Florida (JAX) is not considered a vacation market.

Salt Lake City. Thus, despite the short average Atlanta market distance and the frequency dominance of Delta and Valujet, there is still enough Atlanta market demand to support other carriers offering nonstop or even one-stop or connecting service.[72]

Table 5.9: List of Markets Used in Atlanta Demand Models (airport codes in parentheses)

Atlanta, Georgia to/from	
Fort Lauderdale, Florida (FLL)	Fort Myers, Florida (RSW)
Jacksonville, Florida (JAX)	Louisville, Kentucky (LOU)
Memphis, Tennessee (MEM)	Nashville, Tennessee (BNA)
New Orleans, Louisiana (MSY)	Orlando, Florida (MCO)
Savannah, Georgia (SAV)	Tampa, Florida (TPA)
West Palm Beach, Florida (PBI)	

The passenger numbers for Delta and Valujet show that Delta captured about 67% of the relative market share for the two carriers, with a relative frequency share of about 71%. Although the market share/frequency share S-curve relationship (with a proportionality factor equal to 1.7) predicts a market share closer to 82% for a 71% frequency share, it also assumes that Delta and Valujet offer similar fares, fly similar size and type aircraft and have equal dominance at both Atlanta and the spoke cities. However, as the average fare data listed in Table 5.10 illustrates, Delta's $119.25 average fare paid is almost 89% higher than Valujet's $63.15 average fare paid.

[72] Offering nonstop flights -- and more of them -- becomes increasingly important to airline market share as market distance decreases. Nonstop flights become relatively more attractive than connections because connections occupy a greater proportion of total flight time with shorter market distances. The number of nonstop flights must also be large to reduce the relative attractiveness of other modes of short-haul transportation (e.g. car) for which not as much time need be spend between desired and available departure times.

Table 5.10: Aggregate Descriptive Statistics for Variables Used in Atlanta Demand Models

Atlanta Descriptive Statistics 11 Markets, 53 Observations (All statistics are by market-quarter) Variable	Mean	Standard Deviation	Maximum Value	Minimum Value
DL PASSENGERS	48,581	29,736	111,350	15,952
J7 PASSENGERS	24,384	13,157	52,317	3,560
MARKET PASSENGERS	79,072	45,853	173,507	22,167
POPULATION	1,281,032	919,157	3,485,813	275,467
PER CAPITA INCOME	$ 22,100	$ 3,547	$ 33,729	$ 19,436
DL AVERAGE FARE	$ 119.25	$ 23.11	$ 179.90	$ 80.80
J7 AVERAGE FARE	$ 63.15	$ 12.07	$ 80.00	$ 29.10
MARKET AVERAGE FARE	$ 98.40	$ 14.34	$ 135.40	$ 70.70
DL DAILY NONSTOP FREQ.*	8.06	1.08	9.00	6.00
J7 DAILY NONSTOP FREQ.	3.28	1.00	5.00	1.00
MARKET DAILY NONSTOP FREQ.	12.60	2.90	19.00	7.00
DL FLIGHT TIME (minutes)	76	17	99	53
J7 FLIGHT TIME	77	21	105	50
MARKET FLIGHT TIME	77	17	99	52
DISTANCE (miles)	386	130	581	214
* Each way				

Delta's tremendous fare premium, made possible presumably through its capture of almost all business traffic in the Atlanta markets, as well as the higher fares it undoubtedly charges, seems to corroborate the theory -- evidenced in the Phoenix and Salt Lake City scenarios -- that the traditonal carrier's fare premium increases substantially as the traditional carrier increases its relative dominance over the low-cost carrier for the same competitive market variables. At Phoenix, America West's frequent-flyer program and number of nonstop destinations help it maintain a 34% fare premium over Southwest, even though the latter dominates the number of nonstop frequencies in common short-haul markets. At Salt Lake City, where Delta has some control of business traffic and travel agencies, and maintains a moderate frequency advantage, the average fare paid is 65% higher than Southwest's. And at Atlanta, where Delta has a much larger frequency share than America West at Phoenix or itself at Salt Lake City, and where its dominance of business traffic and travel agencies is widely documented, its passengers pay 89% more than those flying Valujet.

It is especialy remarkable that Delta maintains such a high fare premium over Valujet given the leisure-type nature of the Florida markets which represent almost half the number of the two airlines' flights to and from Atlanta in this study. Usually, leisure passengers are the least likely to select their airline based on flight frequency and marketing gimmicks like frequent flyer programs. Moreover, some of Delta's Atlanta-Florida passengers are undoubtedly Delta frequent-flyers using free tickets. Because neither these passengers nor their free tickets are included in the Atlanta market data, one would assume that most other Atlanta leisure passengers would not pay very much more to fly Delta instead of Valujet. However, the average fares paid (Delta, $119.25 versus Valujet, $63.15) do not reflect this intuition. Thus, Delta must have other strengths in Atlanta (for example, travel agency dominance, reputation and historical loyalty) that attract leisure travelers despite its higher fares.

5.3.2 Modeling Results

The nine demand models for Delta, Valujet and total market in the Atlanta competitve scenario consist of 53 observations (52 if a correction for serial correlation is used) over 11 city-pair markets. Initially, the Atlanta demand models were formulated exactly like those for Phoenix and Salt Lake City. However, after initial demand model results provided very few intuitive elasticity estimates, it was decided to find the most likely cause(s) for the bad results and correct for them in the simplest ways possible.

Compared to the mostly logical Phoenix and Salt Lake City demand model results, there were two major problems with the initial Atlanta demand model results. First, the per capita income elasticity estimates were negative for both airlines and for the total

Atlanta markets. This was thought to be caused by the unusually high per capita income for the West Palm Beach, Florida and Washington, D.C. Dulles Airport market. (The average per capita income of the West Palm Beach and Washington, D.C. metropolitan areas were over $33,000 and $27,000 respectively, while the average Atlanta market per capita income was under $23,000.) Second, Valujet's fare and flight time elasticity ranges were positive and mostly significant. The probable reason for this is that the Florida markets, which generally had the most traffic, are also located the greatest distance from Atlanta. Unfortunately, there were not enough total Atlanta quarterly market observations to counteract this effect.

Each problem with the initial Atlanta demand models was "solved" using a different econometric technique. To ensure better per capita income elasticity estimates, the Atlanta-Washington, D.C. market was removed from the Atlanta scenario as an outlier. However, Atlanta-West Palm Beach remained, and was accounted for by a dummy variable for all Florida vacation markets.[73] The dummy should have repaired some of the biased population and per capita income elasticity estimates by accounting for Atlanta-originating demand. The dummy variable was also added to change the signs of Valujet's average fare and flight time elasticity estimates by removing the amount to which the number of Florida vacation city passengers did not reflect variables already in the demand model.

The elasticity estimates, P-values and adjusted R^2 statistics for the "corrected" set of Atlanta demand models appear in Table 5.11. Notice that a dummy variable has been added to each demand model for both carriers and the total Atlanta market. The dummy variable, which takes a value of "1" if the Atlanta market contains the Florida cities of Fort Lauderdale, Fort Myers, Orlando, Tampa or West Palm Beach and "0" otherwise, reflects

[73] Although it is probably true that the actual explanatory variable elasticities differ between Florida and non-Florida markets (for example, the fare elasticity should be greater for the Atlanta-Fort Lauderdale or Atlanta-Orlando markets than the Atlanta-Memphis and Atlanta-Louisville markets), to be consistent with the other competitive scenarios it was decided to estimate only one set of Atlanta demand models. Thus, the Atlanta demand model elasticity estimates will reflect relatively more aggregation than those for Phoenix or Salt Lake City.

the extra passengers in Florida vacation markets not explained by the other explanatory variables. A cursory examination of dummy variable values and significance indicates that the dummy is positive and significant for Delta and total market passengers, but insignificant for Valujet passengers. The dummy variable will be examined in greater depth in the next section.

Although it seems like the addition of the dummy variable for Florida vacation markets resulted in better specified demand models (at least for Delta and the total Atlanta market), the dummy had little effect on Valujet's estimated positive average fare and flight time elasticities. However, the flight time elasticity in the corrected Delta demand models did turn positive and mostly significant. The removal of data for the Atlanta-Washington Dulles market had some impact on the negative per capita income elasticities for both carriers, but instead of becoming significantly positive, these elasticities only became less negative.

Table 5.11: Atlanta Demand Model Results

		Delta			Valujet			Market		
			P-	R-bar		P-	R-bar		P-	R-bar
Model	Variable(s)	Elasticity	Value	Squared	Elasticity	Value	Squared	Elasticity	Value	Squared
1	FARE	-0.99	0	0.78	0.74	0.0301	0.52	-1.16	0.0001	0.74
	DUMMY	1.04	0.0017		0.28	0.3783		0.83	0.0065	
2	FARE	-0.76	0	0.92	0.37	0.0836	0.82	-0.74	0	0.95
	POPUL	0.6	0		0.83	0		0.69	0	
	DUMMY	0.75	0.0005		-0.15	0.4478		0.46	0.0022	
3	FARE	-0.75	0	0.92	0.44	0.0523	0.82	-0.74	0	0.95
	POPUL	0.6	0		0.79	0		0.69	0	
	PERCAP	0.09	0.7258		-0.46	0.2329		0.03	0.8845	
	DUMMY	0.77	0.0005		-0.13	0.4537		0.47	0.0025	
4	FARE	-0.9	0	0.96	0.39	0.0814	0.83	-0.71	0	0.96
	POPUL	0.56	0		0.71	0		0.66	0	
	PERCAP	-0.44	0.0207		-0.34	0.3717		-0.05	0.7636	
	NSFREQ	1.25	0		0.25	0.1121		0.43	0.0001	
	DUMMY	0.3	0.0028		-0.08	0.6482		0.31	0.0159	
5	POPUL	0.74	0	0.89	0.65	0	0.82	0.77	0	0.93
	PERCAP	-0.28	0.4227		-0.36	0.3571		-0.09	0.7074	
	NSFREQ	0.65	0.105		0.35	0.0324		0.4	0.0145	
	FLTTIME	-0.78	0.1324		0.59	0.1356		-0.44	0.1602	
	DUMMY	0.76	0.003		-0.2	0.3318		0.45	0.0111	
6	FARE	-0.87	0	0.97	0.32	0.1961	0.83	-0.75	0	0.97
	POPUL	0.65	0		0.65	0		0.74	0	
	PERCAP	-0.26	0.1759		-0.45	0.2464		0.03	0.8522	
	NSFREQ	0.88	0.0001		0.3	0.0742		0.28	0.0123	
	FLTTIME	-0.67	0.0184		0.38	0.3631		-0.67	0.0026	
	DUMMY	0.49	0.0003		-0.18	0.3785		0.43	0.0005	
7	POPUL	0.63	0	0.92	0.8	0	0.82	0.72	0	0.94
	PERCAP	0.15	0.5353		-0.44	0.2534		0	0.9658	
	DLFARE	-0.67	0		0.05	0.8334		-0.45	0.0005	
	J7FARE	-0.18	0.2024		0.41	0.1051		-0.09	0.4496	
	DUMMY	0.81	0.0003		-0.13	0.5069		0.35	0.0346	
8	POPUL	0.86	0	0.9	0.61	0	0.82	0.83	0	0.93
	PERCAP	-0.46	0.1655		-0.6	0.2		-0.3	0.2982	
	DLNSFREQ	0.76	0.0434		0.49	0.3073		0.51	0.0899	
	J7NSFREQ	-0.32	0.009		0.33	0.0474		-0.12	0.1938	
	FLTTIME	-0.94	0.0525		0.94	0.077		-0.46	0.2369	
	DUMMY	0.7	0.0021		-0.34	0.174		0.41	0.0296	
9	POPUL	0.57	0	0.96	0.63	0	0.82	0.65	0	0.96
	PERCAP	-0.36	0.0696		-0.39	0.3354		-0.23	0.2284	
	DLFARE	-0.83	0		-0.19	0.4571		-0.58	0	
	J7FARE	-0.17	0.1311		0.51	0.0554		-0.07	0.4896	
	DLNSFREQ	1.22	0		-0.07	0.8355		0.76	0	
	J7NSFREQ	0.02	0.7964		0.32	0.0823		0.1	0.2025	
	DUMMY	0.34	0.0013		-0.08	0.6086		0.16	0.1766	

According to the adjusted R^2 statistics, the explanatory variables in the Atlanta demand models explain Delta and total market demand much better than Valujet demand. Thus, the adjusted R^2 statistic for the Delta demand models (excluding the first model, which tested only average fare and the Florida dummy) ranged from .89 to .97 while the adjusted R^2 for the Valujet demand models remained at about .82 or .83 independent of the explanatory variables used. It is interesting to note that the inability for the same set of explanatory variables to explain as much variance in low-cost carrier demand as traditional carrier demand at Atlanta also occurs at Salt Lake City but does not occur at Phoenix. However, whether this is caused by differences in the way Delta and America West compete against low-cost carriers, imperfections in the data or demand models, or simply random chance, remains unclear.

5.3.3 Comparison of Elasticity Coefficients

The elasticity ranges for the explanatory variables in the Delta, Valujet and total Atlanta market demand models appear in Table 5.12. Although there is little serious multicollinearity between most of the Atlanta demand model variables, the Florida dummy does have a correlation with DLFLTTIME of .77 and a correlation with J7FLTTIME of .82. This occurs because the Atlanta-Florida markets (Fort Lauderdale, Fort Myers, Orlando, Tampa and West Palm Beach) are a greater distance from Atlanta on average than the other Atlanta markets. As Valujet fares are set mainly by distance and are relatively insensitive to competitive pricing (because Valujet is likely the price leader in its markets), the correlation between Valujet fares and flight time, which equals .73 is also somewhat high.

In common with the Phoenix and Salt Lake City scenarios, the ranges for the estimated total Atlanta market elasticities are a weighted average of the elasticities for all individual carriers in the market. As mentioned earlier, Atlanta is the only competitive scenario for which the main traditional and low-cost carriers were not alone in providing nonstop service in all local hub markets. However, as Delta and Valujet combined to serve 92% of Atlanta market passengers, the service offerings of other carriers should have little influence on Atlanta market elasticity numbers.

Table 5.12: Elasticity Ranges for Atlanta Demand Models

Explanatory Variable	Delta Air Lines Passengers	Valujet Airlines Passengers	Total Market Passengers
Spoke City Population	.56 to .86	.61 to .83	.65 to .83
Spoke City Per Capita Income	-.46 to .15	-.34 to -.60	-.30 to .03
Average Fare	-.67 to -.99	.32 to .74	-.71 to -1.16
Quarterly Nonstop Frequencies	.65 to 1.25	.25 to .35	.28 to .43
Scheduled Flight Time	-.67 to -.94	.38 to .94	-.44 to -.67
Average Cross-Fare	-.17 to -.18	-.19 to .05	N/A
Quarterly Nonstop Cross-Frequencies	-.32 to .02	-.07 to .49	N/A
Florida Vacation Market Dummy	.30 to 1.04	-.34 to .28	.16 to .83

As Table 5.12 shows, the Atlanta market elasticity ranges are weighted heavily towards Delta's elasticities, especially for per capita income, average fare, flight time and the Florida dummy. This reflects Delta's market share dominance in Atlanta and probably in most of the Atlanta spoke cities as well. Only the nonstop frequency elasticity range for the total Atlanta market is weighted towards Valujet. Apparently, this occurs because the number of Delta frequencies in individual Atlanta markets is relatively stable throughout the study period, while Valujet and carriers like KIWI and Air South seem to have been adding flights. Thus, Table 5.10 shows that while Delta maintained the same amount of daily frequencies in 8 out of the 11 Atlanta markets, Valujet did so in only 5. Because Valujet was generally expanding its presence in Atlanta during this time, it seems that the estimated total Atlanta market nonstop frequency elasticities are mainly picking up the effects of additional Valujet, rather than Delta flights.

Using the same reporting procedure as the Phoenix and Salt Lake City scenarios, the differences in the estimated elasticity ranges for individual explanatory variables for Delta and Valujet are interpreted below using the Atlanta scenario descriptive statistics in Table 5.10 and the discussion of local airline market choice and econometric modeling in Chapters 3 and 4.

- **Population.** The values for the population elasticity range are about the same for Delta (.56 to .86) as for Valujet (.61 to .83). This means that the same proportional change in spoke city population has about the same proportional effect on the number of Delta and Valujet passengers. This is an unusual result considering that the estimated popoulation elasticities for the traditional carrier at Phoenix and Salt Lake City were clearly larger than those for the low-cost carrier. However, a couple reasons can be offered for the Atlanta numbers:

1. It was assumed that one of the main reasons why population changes would have a stronger proportional impact on the number of traditional airline passengers was that the traditional airline catered mainly to time-sensitive, price-inelastic business travelers. This passenger pool is not as likely (as low-cost airline passengers) to make or change travel plans based on the values of transport supply variables like airfare. This is why it takes exogenous changes in the local hub markets -- changes in population or per capita income, for example -- to significantly increase or decrease the number of traditional airline passengers.

However, unlike the majority of Phoenix and Salt Lake City markets, almost half of the Atlanta markets consist of mainly leisure-oriented traffic flying between Atlanta and

Florida resort destinations. This implies that at Atlanta, the traditional and low-cost airlines carry a more similar traffic mix than at Phoenix and Salt Lake City. It follows that changes in the level of socioeconomic variables like population should affect Delta and Valujet about equally, which the estimated population elasticity ranges reflect.

2. As mentioned in Section 5.1.2, the population and per capita income values for the Florida cities should not have much impact on the number of Atlanta-Florida market passengers since most of them probably begin their trips in Atlanta. The values for the Florida vacation markets, however, may confuse the "true" differential impact of population and per capita income on the number of Delta and Valujet passengers derived from the 6 out of 11 other Atlanta markets. In this case, the estimated population elasticity ranges may reflect substantial bias and although they are measured at about the same values for the traditional and low-cost carrier, no firm conclusions can be drawn.

- **Per Capita Income.** The estimated per capita income elasticity range is larger for Delta (-.46 to .15) than for Valujet (-.34 to -.60), although both sets of numbers make little sense. All else equal, Delta and Valujet should realize an increase in passengers from an increase in the per capita income of the population in Atlanta markets. Looking at individual Atlanta market data in Appendix D, it seems like there are two possiblities for the counterintuitive per capita income elasticitiy estimates:

1. As mentioned in Section 5.3.2, the Atlanta-Washington, D.C. market was removed from the set of markets used to estimate the Atlanta demand models because of the relatively high population and per capita income numbers for the Washington, D.C. area. However, despite the even higher per capita income numbers for West Palm Beach, the Atlanta-West Palm Beach market was retained in the demand models because a dummy was included for Florida markets. Recall that the dummy was included because the usual set of explanatory variables in the local hub demand models could not account for the resort status of many Florida destinations. One would expect that the values for the other explanatory variable elasticities would become unbiased because the demand models

would no longer be misspecified. However, it seems that the small number of Atlanta market observations combined with the extremely high per capita income in the West Palm Beach area had a stronger effect than the dummy, and prevented the estimation of "proper" carrier and market per capita income elasticities.

2. As with population, the per capita incomes of Florida vacation destinations should be mostly irrelevant to the number of Atlanta-Florida market passengers since most Atlanta-Florida traffic probably originates at Atlanta. Thus, there is some chance that the per capita incomes of the Florida vacation destinations confuse the "true" differential impact (measured by the relationship in non-Florida markets) of changes in per capita income on the number of passengers flying both airlines as well as the total Atlanta market. Unfortunately, it appears that the quarterly population and per capita income of the Atlanta area (as opposed to just the spoke cities) should have been considered as explanatory variables in the Atlanta demand models.

- **Average Fare.** The values for the average fare elasticity range are not directly comparable. Although the Delta average fare elasticities are within an acceptable and intuitive range (-.67 to -.99), the Valujet average fare elasticities, which range from .32 to .74, are not. In fact, the Valujet fare elasticities actually imply that Valujet will carry more passengers when it either raises its fares or its mix of passengers shifts more towards business traffic; neither explanation makes sense.

Although meaningful comparisons between the Delta and Valujet estimated average fare elasticities are not possible, it is instructive to discuss each individually. The estimated Delta average fare elasticities are all in the price-inelastic range because their absolute values are less than one. This means that a 1% change in Delta's average fare has less than a 1% change in Delta's traffic, all else equal, and seems to confirm the preference by relatively price-insensitive business passengers for Delta in the Atlanta area and throughout the Southeast.

It is interesting that the estimated fare elasticities for Delta passengers were all in the price-inelastic range throughout the study period considering that almost half the Atlanta markets are to Florida vacation destinations. Because the traffic mix in these markets should be weighted towards more price-elastic leisure passengers (who might drive to Florida or take their vacations somewhere else if fares are too high), one would expect the price-elasticity for Florida passengers to be higher for all carriers, including Delta. One must conclude that if the Delta demand models were run only on non-Florida vacation markets, Delta's estimated average fare elasticities would be even more inelastic than in the aggregated models. Indeed, running several regressions on non-Florida vacation markets only proved this to be the case.[74]

There are several possible reasons why positive average fare elasticities were estimated for Valujet. According to the individual Atlanta market data in Appendix D, Valujet fares increase more strictly with distance but are much less influenced by other airline competition than Delta fares. Unfortunately, the largest Atlanta markets in the sample (Orlando, Tampa, Fort Lauderdale) are also the markets which are farthest apart, so one would expect that these markets would be large regardless of the fares. Apparently, the dummy variable for Florida markets did not work as well for Valujet as it did for Delta and for the total Atlanta market.

An additional problem with the Valujet fares is is their relative lack of movement over the study period (see Appendix D). In such a small pooled data set (recall that the Atlanta sample combines 11 city-pair markets over a <u>maximum</u> of 6 quarters per market), it is very difficult for a regression to account for average fare movements in the same market over time because differences between markets tend to be more measureable, and average fare is not as good a predictor of cross-sectional demand as variables like population and flight frequency.

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[74] Delta fare elasticities in non-Florida markets <u>only</u>, ranged from -.29 to -.73. Delta fare elasticities in Florida vacation markets <u>only</u>, ranged from -.75 to -1.30. As one would expect, Delta fare elasticities for <u>all</u> markets were in between these two ranges. As stated in the text, the Delta all market range was -.67 and -.99.

- **Nonstop Frequency.** The values for nonstop frequency elasticity are much higher for Delta (.65 to 1.25) than for Valujet (.25 to .35). These numbers mean that a 1% increase in the number of quarterly Delta or Valujet nonstop frequencies in the average Atlanta market have a much greater proportional effect on the number of Delta passengers.

At first glance, the Delta/Valujet frequency differential seems odd considering that the generic market share/frequency share relationship from Chapter 3 would predict that Delta have a much lower frequency elasticity than Valujet given its 8.06 daily each way nonstop frequencies to Valujet's 3.28 in the average Atlanta market. Recall that the main reason for this is that an additional Valujet flight will increase the number of Valujet round-trip opportunities by a much greater proportion than an additional Delta flight. For example, at the above mean numbers of daily flights for each carrier, an additional Delta flight will increase the number of Delta round-trip opportunities by about 26% $(((9.06)^2 - (8.06)^2)/(8.06)^2 = .264)$ while an additional Valujet flight will increase the number of Valujet round-trip opportunities by about 70% $(((4.28)^2-(3.28)^2)/(3.28)^2 = .703)$.

Although the reversal of the "proper" Delta and Valujet frequency elasticities seems to challenge the ability of the theoretical market share/frequency share relationship to robustly predict relative carrier frequency elasticities in a competitive local hub market, it is also true that Atlanta market characteristics are different in many ways from those of Phoenix and Salt Lake City. These differences can be used to explain why the estimated Delta and Valujet frequency elasticities seem reversed.

One difference is that while the traditional carrier average aircraft size at Phoenix and Salt Lake City is not much larger than the low-cost carrier's, Delta's average aircraft size at Atlanta is much larger than that for Valujet. According to the June, 1994 O.A.G., Valujet flew all 30,40 and 50 series DC-9 aircraft with about 88 to 110 seats each on its Atlanta routes while Delta flew a wide variety of narrow- and widebody aircraft, almost all with significantly higher seating capacities than a DC-9.[75] In the Atlanta-Tampa market, for example, which admittedly has a large proportion of widebody aircraft compared to the other Atlanta markets, the average Delta aircraft had about 219 seats in June, 1994.[76] In this context, it is not surprising that regardless of any Delta/Valujet frequency differences, an additional Delta flight should carry many more passengers than an additional Valujet flight.

Another factor that would help explain why Delta's frequency elasticities were estimated so much higher than Valujet's is simply the latter's status as a low-frequency, low-fare airline. Although the estimated Valujet frequency elasticity range (.25 to .35) does show some positive relationship between additional Valujet flights and passengers, the elasticities are very low, especically with respect to Valujet's relative position on the market share/frequency share curve in Atlanta markets. This suggests that Valujet's passengers are attracted almost entirely by Valujet's fares and that additional Valujet frequencies should only stimulate additional Valujet traffic to the extent that the current number of Valujet flights are not accommodating all the traffic that wants to fly at Valujet's fares (a number that should also be increasing over time as Valujet increases market presence).

- **Flight Time.** As with average fare, the estimated Delta and Valujet flight time elasticities are not directly comparable. While the flight time elasticity range for Delta (-.67 to -.99) is reasonable, the flight time elasticity range for Valujet (.38 to .94) is not. In fact, the Valujet elasticites actually imply that a 1% increase in flight time leads to between a .38% and .94% <u>increase</u> in the number of Valujet passengers. Obviously, this result does not make intuitive sense.

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[75] Because the O.A.G. did not have seating charts for Valujet's DC-9's, it was assumed that Valujet DC-9's had the same number of seats as Northwest's DC-9's, whose seating capacities were reported. Thus, it is Northwest's DC-9's that actually had between 88 and 110 seats each in June, 1994.

[76] Delta figures calculated from the June, 1994 O.A.G. as the average of Delta aircraft type seating capacities for all aircraft types used by Delta in the Atlanta-Tampa market (where the seating capacity of each aircraft type is itself an average of the seating capacities of the various configurations of each aircraft type) weighted by the number of daily Delta Atlanta-Tampa flights by aircraft type.

Although meaningful comparisons between the Delta and Valujet estimated flight time elasticities are not possible, it is instructive to discuss each elasticity range individually. The Delta flight time elasticities, for example, are all inelastic, because longer market flight times do not reduce the amount of Delta passengers by a proportionate amount.

The origin of positive flight time elasticities for Valujet most likely relfects the same causes as Valujet's positive estimated average fare elasticities. That is, because most of the largest Atlanta markets in the sample are also the greatest distance from Atlanta (e.g. Fort Lauderdale, Orlando and Tampa), there is a positive correlation between the number of Valujet passengers and market flight time. More importantly, the elasticity range estimated for Valujet's Florida vacation destinations implies that the dummy is not significantly different from zero. Thus, while the Florida dummy corrects for the strong demand in Delta's Atlanta-Florida markets (thus allowing more unbiased estimation of Delta flight time elasticities), it has no effect on Valujet's Atlanta-Florida markets, allowing the positive correlation between Valujet flight time and passengers to remain, in some sense "unchecked."

Another possible reason why positive flight time elasticities are estimated for Valujet and not for Delta concerns the relative importance of frequency share with increased market distance. In general, an airline with an inferior frequency share should realize more market share as market distance increases because the amount of time between flights become a decreasing proportion of total travel time. As Figure 5.3 shows, there does not seem to be any relationship between Delta/Valujet relative frequency share and Atlanta market distance. Thus, it is possible that the additional passengers that Valujet realizes on its longer routes are partly the result of its frequency share parity with Delta. This would help explain Valujet's positive esitmated flight time elasticities.

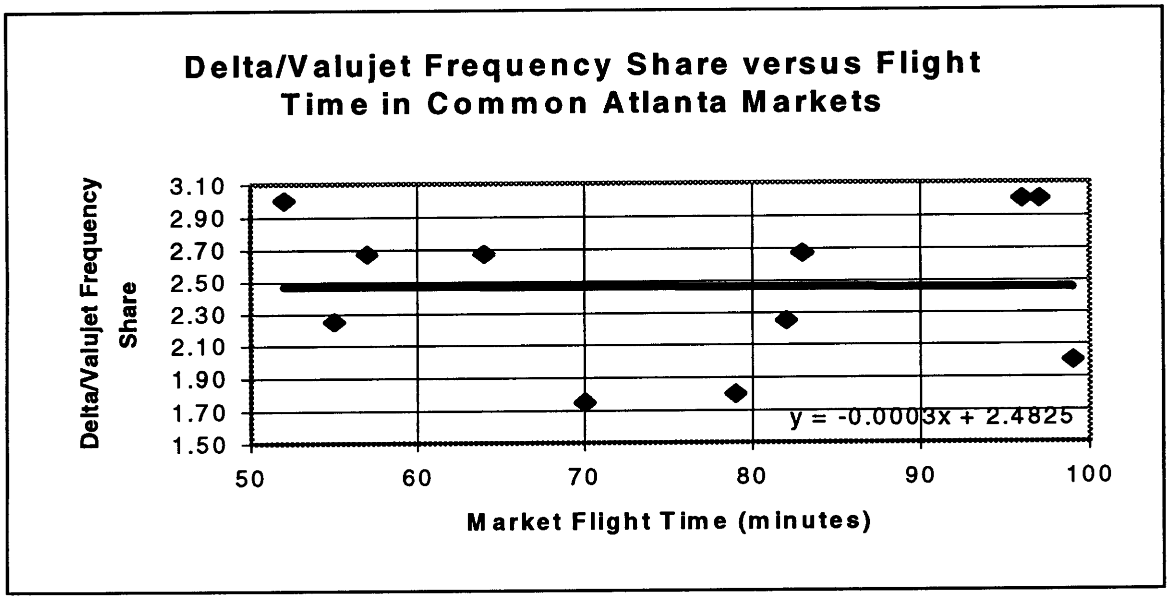

Figure 5.3: Delta/Valujet Frequency Share versus Flight Time in Common Atlanta Markets

- **Cross-Fare.** The estimated cross-fare elasticity ranges are -.17 to -.18 for Delta passengers and -.19 to .05 for Valujet passengers. This means that, all else equal, a 1% increase in Valujet fares should decrease the number of Delta passengers by between .17% and .18%, while a 1% increase in Delta fares has no appreciable effect on the number of Valujet passengers.

The Delta numbers (-.17 to -.18), which have the same sign as the America West cross-fare elasticities in the Phoenix scenario, suggest that Delta matches changes in Valujet's fares.[77] Otherwise when Valujet raises its fares, for example, Delta should realize an increase in passengers because the ratio of its fares to Valujet's fares will decrease. Unfortunately, price matching behavior precludes the estimation of true cross-fare elasticities, i.e. the change in the number of Delta passengers when Valujet increases or decreases its fares but Delta does not.

[77] Whether Delta matched the actual fares offered by Valujet, or just changed its fares to maintain about the same ratio of its fares to Valujet's when Valujet changes its fares it unclear.

The Valujet cross-fare elasticities (-.19 to .05), by contrast, suggest that changes in Delta fares have no statistically significant effect on the number of Valujet passengers. This makes sense considering that (1) as the price leader in its Atlanta markets, Valujet probably does not respond to other airline's fare changes[78] and (2) as a relatively unknown low-cost carrier with comparatively few Atlanta market frequencies, one would expect that Valujet's passengers are almost completely stimulated by its low fares. In other words, most Valujet passengers come from a different passenger market than the people who fly Delta.

- **Cross-Frequency.** The values for cross-frequency elasticity make sense for both Delta passengers (-.32 to .02) and for Valujet passengers (-.07 to .49). An additional Valujet flight most likely has a slight negative impact on the number of Delta passengers because Valujet may recapture some passengers who were denied reservations on Valujet and were forced to "sell up" to higher Delta fares. With additional Valujet flights, this "spill" obviously decreases. Notice also that the low Delta cross-frequency elasticity implies that most of the new traffic stimulated by additional Valujet flights is "new" in the sense that, absent Valujet, these passengers would not have flown Delta.

An additional Delta flight seems to result in a slight increase in the number of Valujet passengers, although this cross-frequency effect is never statistically significant. As with the Phoenix scenario, where additional America West flights were found to increase the number of Southwest passengers, it is probably best to blame multicollinearity, the aggregation level of regression data, or the small sample size for the counterintuitive results.

- **Florida Dummy.** As mentioned in Section 5.3.2, the Florida dummy represents aspects of Atlanta-Florida markets not captured in any of the basic demand model formulations. The value for the dummy variable used to represent Atlanta-Florida

[78] Notice that this makes the Valujet cross-fare elasticity estimates a lot more "true" than those for Delta.

vacation markets is positive and significant for Delta (and Atlanta-Florida markets as a whole) but of unclear sign and statistical insignificance for Valujet. For Delta, the value of the Florida dummy is estimated between .30 and 1.04. To interpret these numbers, note first that to formulate a multiplicative demand model using a dummy variable, the equation must raise e [79] by the value of the dummy coefficient multiplied by the dummy itself:[80]

$$D = P^{\alpha} e^{\beta Dummy} \tag{5.2}$$

where

D	is total market traffic
P	is the average fare paid
α	is the fare elasticity of demand
β	is the dummy value
e	is the inverse of the natural logarithm

Once the above equation is transformed into log-linear form and estimated using ordinary least-squares, the value for the dummy coefficient can be placed back into the original demand equation, where it acts as the power by which e is raised when the dummy variable equals one. This final number -- e raised to the power of the estimated dummy coefficient -- is the important one. Its value is interpreted as the proportion by which demand is higher or lower (depending on the sign of this final number) for an observation with a dummy variable equal to one.

Thus, the range of estimated Delta dummy coefficient values (.30 to 1.04) translate into final values of 1.35 to 2.83, and mean that Delta's Florida vacation markets have demand between 35% and 183% higher than Delta's non-Florida vacation markets, all else equal. By contrast, the range of the estimated Valujet dummy coefficient values (-.34 to

[79] e is an irrational number whose value is about 2.718. Its significance is that it is the inverse of the natural logarithm function. In other words, the natural logarithm of e is one.

[80] Note that this fictitious demand function was kept deliberately simple to focus attention on the properties of the dummy variable.

.28) translate into final values of .71 to 1.32, and mean that Valujet's Florida vacation markets have demand between 29% lower and 32% higher than Valujet's non-Florida vacation markets. Thus, the effect of the dummy is insignificantly different from zero for Valujet. In other words, Valujet's Florida markets have no demand not already accounted for by the basic demand model variables.

Because Florida vacation destinations should have higher demand than other Atlanta markets across carriers, it is hard to understand why the Florida dummy is positive and significant for Delta's Atlanta-Florida markets, but not so for Valujet's. A possible answer, which requires consultation of the individual Atlanta market data in Appendix D, is that with very low fares and nonstop frequencies that do not seem to vary much by market distance or location, Valujet simply could not handle as much extra Florida demand as Delta. Another possibility is that the two Atlanta-Florida markets that had significantly less individual carrier and total market passengers than the other Atlanta-Florida markets had a stronger negative impact on dummy estimation for Valujet, perhaps because the markets' size was disproportionately smaller for Valujet than for Delta.

* * *

This chapter has presented the results from the estimation of local hub market demand models for the traditional airline, low-cost airline and total market at traditional airline hub airports in Phoenix, Salt Lake City and Atlanta. Individual airline and total market elasticity of demand estimates have been presented and summarized for the explanatory variables included in the demand models. Then, differential traditional and low-cost airline elasticity ranges were interpreted for each competitive scenario using individual airline and total market variable descriptive statistics and insights from the previous discussion of local market airline choice. A final cross-scenario comparison of traditional and low-cost airline elasticity estimates is the subject of the next chapter.

6. Summary and Interpretation of Elasticity Differentials

The traditional and low-cost carrier elasticities calculated for the Phoenix, Salt Lake City and Atlanta competitive scenarios in Chapter 5 are meant to provide an estimate of the effects of changes in basic airline demand variables on the number of actual traditional and low-cost passengers in the same sets of local hub markets. Although the estimated elasticities were interpreted in detail for each competitive scenario, there was little attempt made to explore patterns in traditional and low-cost carrier elasticities across competitive scenarios.

The focus of Chapter 6 is on identifying and interpreting these patterns of common elasticity estimates. For each of the explanatory variables used in the traditional and low-cost carrier demand models, a summary of the carrier elasticity estimates is provided, and the observed pattern of elasticity differentials across competitive scenarios is described for the traditional and low-cost carrier. The elasticity differentials are interpreted as a group using the same logic used to interpret individual traditional and low-cost carrier elasticity estimates in each competitive scenario.

6.1 Population

For all scenarios except Atlanta (for which spoke city population was shown to be unimportant to passenger demand in Florida markets), changes in spoke city population have a stronger proportional effect on the amount of traditional carrier traffic than low-cost carrier traffic. Thus, **the size of the population served by the spoke airport seems to have a greater effect on the number of traditional carrier passengers**. This is evident from Table 6.1, which shows the ranges of the estimated population elasticities for the traditional and low-cost carrier in all competitive scenarios.

Table 6.1: Comparison of Traditional and Low-Cost Carrier Population Elasticity Ranges

Competitive Scenario	Traditional Carrier	Population Elasticity Range	Low-Cost Carrier	Population Elasticity Range
Phoenix	America West	.26 to .51	Southwest	.09 to .21
Salt Lake City	Delta	.40 to .68	Morris Air/Southwest	.31 to .51
Atlanta	Delta	.56 to .86	Valujet	.61 to .83

Although Chapter 5 listed several possible reasons why traditional carriers should realize greater gains from increases in spoke city population, the most likely one is that traditional and low-cost carrier passengers come from relatively different passenger market segments. In local hub markets, traditional carrier passengers travel more often on business than low-cost passengers, and thus tend to value the traditional carrier's superior flight frequency, frequent-flyer program and on-board service. Moreover, because much business travel is fare-independent, the number of business travelers is determined more by exogenous demographic and economic factors than by attempts to "grow" the market through lower airfares, for example. By contrast, low-cost airline passengers are more likely to be traveling on vacation or visiting friends and relatives. The low-cost airline can use lower fares to stimulate travel by these price-elastic passengers, making the potential spoke city population base less important above a certain minimum threshold.

6.2 Per Capita Income

The ranges of the per capita income elasticities for traditional and low-cost carriers across competitive scenarios are listed in Table 6.2. The counterintuitive per capita income elasticity ranges estimated for the traditional and low-cost carrier in the Salt Lake City and Atlanta scenarios make it difficult to state conclusively the relative direction and size of the per capita income differential across competitive scenarios, much less make any interpretations.[81] However, based on the higher quality of the Phoenix scenario data, **the per capita income of the region served by the spoke airport probably has a stronger effect on the number of traditional carrier passengers than the number of low-cost carrier passengers.**

In the Phoenix scenario, changes in per capita income had a much larger proportional effect on the number of traditional carrier passengers than the number of low-cost carrier passengers. This is thought to occur for two reasons. First, greater per capita incomes are positively correlated with increased employee travel, and thus with the increased importance of real and perceived on-ground and in-flight services for which the traditional carrier usually offers a superior product. Second, as per capita income increases, people may be more willing to spend a little more for the real or perceived better comfort and service of the traditional carrier.

Table 6.2: Comparison of Traditional and Low-Cost Carrier Per Capita Income Elasticities

Competitive Scenario	Traditional Carrier	Per Capita Income Elasticity Range	Low-Cost Carrier	Per Capita Income Elasticity Range
Phoenix	America West	1.27 to 1.84	Southwest	.18 to .92
Salt Lake City	Delta	.19 to .59	Morris Air/Southwest	.33 to .74
Atlanta	Delta	-.46 to .15	Valujet	-.34 to -.60

[81] Recall that in the Salt Lake City scenario, the low-cost carrier average fare and passenger data were manufactured based on a small amount of real data. Specifically, the number of low-cost carrier passengers is overestimated, which should result in higher elasticities for positive passenger number/explanatory variable relationships and lower elasticities for negative relationships. This may be why higher per capita income elasticities were calculated for the low-cost carrier there. In the Atlanta scenario, a small sample size, the presence of irrelevant variables and possible model specification seem to blame for sign indeterminate or distinctly negative per capita income elasticities for the traditional and low-cost carrier.

6.3 Average Fare

Although the differential impact of changes in average fare is not completely clear from the traditional and low-cost carrier average fare elasticity ranges in Table 6.3, **the number of passengers carried by the traditional airline is probably affected proportionately less by changes in traditional airline airfares than the number of low-cost airline passengers is affected by changes in low-cost airline airfare.**[82] Again, this contention is based primarily on the results of the Phoenix scenario, in which the price elasticities for the traditional carrier were estimated as much more inelastic than those for the low-cost carrier. In local hub markets, traditional carrier passengers are less price elastic than low-cost carrier passengers because (1) the traditional carrier handles the greater proportion of business traffic, which tends to value service quality over airfares and (2) local market seats are more scarce on the traditional carrier because of its focus on connecting traffic; thus, local passengers must pay higher fares for traditional carrier seats on higher demand flights.

Table 6.3: Comparison of Traditional and Low-Cost Carrier Average Fare Elasticities

Competitive Scenario	Traditional Carrier	Per Capita Income Elasticity Range	Low-Cost Carrier	Per Capita Income Elasticity Range
Phoenix	America West	-.34 to -1.09	Southwest	-1.37 to -3.29
Salt Lake City	Delta	-.91 to -1.22	Morris Air/Southwest	-.05 to -.62
Atlanta	Delta	-.67 to -.99	Valujet	.32 to .74

82 Again, the average fare elasticities estimated in the Salt Lake City and Atlanta competitive scenarios do not support this statement. As mentioned, however, there are extraneous circumstances in each. For Salt Lake City, the manufacture of the Morris Air fare data, along with the possibility that Delta's low Salt Lake City load factors allowed the effects of matching some of Morris Air's/Southwest's fares to stimulate an unusually high amount of traffic, may explain why Delta's fare elasticities were higher than those for Morris/Southwest. In Atlanta, Valujet fare elasticities were actually positive because Valujet's fares are based strictly on distance and the largest Atlanta markets in the sample are also the farthest apart. Also, there was very little time series data in the Atlanta sample. Apparently, more time series data is necessary for estimating the "true" demand/average fare relationship.

6.4 Nonstop Frequency

Estimated traditional and low-cost carrier nonstop frequency elasticities do not seem to depend very much on whether the carrier is traditional or low-cost. Rather, **differential nonstop frequency elasticities seem to mostly reflect the relative positions of the traditional and low-cost carrier on the S-shaped market share/frequency share curve.** Specifically, the carrier with fewer nonstop frequencies always has the greater nonstop frequency elasticity because an additional flight will increase its frequency share disproportionately as compared to the carrier with more nonstop frequencies.

As the tables of descriptive statistics for each scenario in Chapter 5 and Table 6.4 illustrate, the carrier with more nonstop frequencies always has the lower nonstop frequency elasticity. Moreover, this does not depend on whether the carrier is traditional or low-cost. In Phoenix, the traditional carrier has the greater nonstop frequency elasticity, while in Salt Lake City this distinction belongs to the low-cost carrier. The exception is Atlanta, where the larger aircraft flown by the traditional carrier (Delta) seem to allow it much higher frequency elasticities than the low-cost competitor (Valujet) despite its frequency dominance in common markets.

Table 6.4: Comparison of Traditional and Low-Cost Carrier Nonstop Frequency Elasticities

Competitive Scenario	Traditional Carrier	Nonstop Frequency Elasticity Range	Low-Cost Carrier	Nonstop Frequency Elasticity Range
Phoenix	America West	.45 to .74	Southwest	.17 to .34
Salt Lake City	Delta	.25 to .61	Morris Air/Southwest	.64 to .67
Atlanta	Delta	.65 to 1.25	Valujet	.25 to .35

Although traditional and low-cost carrier nonstop frequency elasticities seem mostly determined by relative frequency shares, they can be tempered by other relationships. For example, because relatively more low-cost carrier passengers fly the low-cost airline for reasons other than schedule, additional low-cost carrier flights should not have the same stimulative effect as additional flights by the traditional carrier. Also, to the extent that the traditional or low-cost carrier are spilling passengers due to high load factors, additional traditional or low-cost carrier flights may have a greater effect on the number of passengers each carrier is able to accommodate.

6.5 Flight Time

The ranges of the flight time elasticities for traditional and low-cost carriers across competitive scenarios are listed in

Table 6.5. The counterintuitive flight time elasticity ranges estimated for the traditional and low-cost carrier in the Salt Lake City and Atlanta scenarios make it difficult to intrepret the relative direction and size of the flight time elasticity differential across competitive scenarios.[83]

Table 6.5: Comparison of Traditional and Low-Cost Carrier Flight Time Elasticities

Competitive Scenario	Traditional Carrier	Nonstop Flight Time Elasticity Range	Low-Cost Carrier	Nonstop Flight Time Elasticity Range
Phoenix	America West	-.64 to -.73	Southwest	-1.05 to -1.43
Salt Lake City	Delta	.60 to 1.51	Morris Air/Southwest	-.05 to -.80
Atlanta	Delta	-.67 to -.94	Valujet	.38 to .94

[83] For a description of why the flight time elasticities calculated for the Salt Lake City and Atlanta scenarios are difficult to explain, please see the sections on the Salt Lake City and Atlanta competitive scenarios in Chapter 5.

However, based on the better quality of Phoenix scenario data and results, **changes in the number of traditional carrier passengers are probably less elastic to changes in flight time than is the number of low-cost carrier passengers**. Traditional carrier flight time elasticities should be more inelastic than low-cost carrier flight time elasticities because (1) as flight time increases, so does the relative importance of frequent-flyer miles and on-board service to passengers choosing a carrier -- categories for which the traditional carrier is usually regarded as preferred -- and (2) travel agents may be more likely to book the traditional carrier over longer distances because its absolute fare differential over the low-cost carrier generally increases with distance.

6.6 Cross-Fare

Changes in the number of traditional carrier passengers due to changes in the average fare of the low-cost carrier mostly reflect the traditional carrier matching changes in the low-cost carrier's average fares, while changes in the number of low-cost carrier passengers due to changes in traditional carrier average fare seem to depend more on whether and by how much the traditional and low-cost carrier are regarded as substitutes in the same local hub markets. This is why **the cross-fare elasticities of low-cost carrier average fares on traditional carrier passengers are generally negative while the cross-fare elasticities of traditional carrier average fares on low-cost carrier passengers are positive if the low-cost carrier is perceived as being substitutable for traditional carrier service and zero if the traditional and low-cost carrier are not**. Table 6.6 makes it clear that this statement is particularly applicable to the Phoenix and Atlanta scenarios, rather than to Salt Lake City, where Delta and Morris Air/Southwest cross-fare elasticities seem to have signs opposite to that expected.

Table 6.6: Comparison of Traditional and Low-Cost Carrier Cross-Fare Elasticities

Competitive Scenario	Traditional Carrier	Cross-Fare Elasticity Range	Low-Cost Carrier	Cross-Fare Elasticity Range
Phoenix	America West	-.3 to -1.16	Southwest	.99 to 1.11
Salt Lake City	Delta	.30 to .32	Morris Air/Southwest	-.39 to -1.4
Atlanta	Delta	-.17 to -.18	Valujet	-.19 to .05

In Phoenix, where Southwest is the price leader and is regarded as a close substitute for America West for many passengers, changes in Southwest fares have a negative effect on America West passengers because America West matches the fare changes. By contrast, changes in America West fares have a strong positive effect on the number of Southwest passengers because Southwest does not generally match America West fare changes. In Atlanta, where Valujet is the price leader but is <u>not</u> regarded as a close substitute for Delta, changes in Valujet fares have a mild negative effect on Delta passengers as Delta may selectively match Valujet fare changes. Changes in Delta fares do not seem to have a strong effect on the number of Valujet passengers, presumably because Delta fares are already so much higher than Valujet fares that reducing or increasing a little relative to Valujet fares is not noticeable in local Atlanta markets.

6.7 Cross-Frequency

Changes in the number of traditional or low-cost carrier passengers due to changes in the number of traditional or low-cost carrier frequencies, respectively, seem to depend both on the frequency shares of the traditional and low-cost carrier and the substitutability between the two. In general, however, **the cross-frequency elasticities of low-cost carrier frequencies on traditional airline passengers have about the same negligible effect as the cross-frequency elasticities of traditional airline frequencies on the number of low-cost airline passengers**. This is evident from Table 6.7, which shows the cross-frequency elasticity ranges for traditional and low-cost carriers across the competitive scenarios.

In Phoenix, for example, where America West and Southwest are regarded as substitutes by many passengers, the effect of additional Southwest flights on America West passengers is hardly perceptible because Southwest already has so many more flights than America West. In Salt Lake City, the effect of additional Morris/Southwest flights on Delta passengers is not significantly different from zero because Delta is clearly the preferred carrier. Thus, unlike Morris/Southwest, Delta is able to take some previous Morris/Southwest passengers when it adds its own flights. Unlike its low-cost counterparts, additional Valujet flights in Atlanta markets seem to have a slightly negative impact on the number of Delta passengers, probably because Delta's average fares are so much proportionally higher.[84]

Table 6.7: Comparison of Traditional and Low-Cost Carrier Cross-Frequency Elasticities

Competitive Scenario	Traditional Carrier	Cross-Frequency Elasticity Range	Low-Cost Carrier	Cross-Frequency Elasticity Range
Phoenix	America West	-.05 to -.06	Southwest	.18 to .52
Salt Lake City	Delta	-.09 to .08	Morris Air/Southwest	-.03 to -.2
Atlanta	Delta	-.32 to .02	Valujet	-.07 to .49

*   *   *

This chapter has summarized and interpreted the patterns of traditional and low-cost carrier elasticity estimates observed for local hub markets in Phoenix, Salt Lake City

[84] Note that the effect of additional America West flights on the number of Southwest passengers in Phoenix is positive and statistically significant. As mentioned in Chapter 5, unless a large proportion of Phoenix market passengers fly America West one way and Southwest the other, there is no intuitive explanation for the positive cross-frequency elasticities. They are probably the result of multicollinearity or model misspecification.

and Atlanta. An examination of these differential elasticities has revealed that, despite some instances where an elasticity did not quite make sense for a specific traditional or low-cost carrier in a specific competitive scenario, there do seem to be patterns to the effects of changes in basic airline demand variables on the number of traditional and low-cost carrier passengers.

7. Conclusions

7.1 Research Findings

This thesis has focused on modeling the passenger demand for traditional and low-cost airlines where they compete in the same local hub markets. Demand models for the traditional and low-cost airlines were developed separately to test the theory -- prevalent among many students of the airline industry -- that the passengers who fly traditional and low-cost airlines belong to two different passenger market segments. Specifically, traditional airline passengers are said to be more sensitive to airline service quality characteristics like flight frequency, on-board service and frequent-flyer programs, while low-cost airline passengers are supposedly more sensitive to price.

These assumptions were tested by calibrating local hub market demand models for both carrier types using the same sets of basic explanatory variables: population, per capita income, average fare, nonstop frequency, flight time, cross-fare and cross-frequency. Demand models were estimated for the total market as well, to determine the importance of changes in each individual carrier's explanatory variables to total market demand, and to account for the effects of other market carriers whose individual effects were not otherwise included in the models. The goal of the calibration process was to find and compare the explanatory variable elasticity estimates between the traditional and low-cost carrier to see if changes in the explanatory variables seemed to have different effects on passenger demand depending on carrier type. Explanatory variable and passenger demand descriptive statistics for individual carriers and the total market were compiled to help illustrate the competitive situations, and to help explain why cross-carrier elasticity differentials might exist.

Individual carrier and total market demand models were developed for three "competitive scenarios" -- traditional airline hubs at which the traditional airline faces significant but distinct competition from low-cost carriers in local hub markets. The three competitive scenarios -- America West Airlines versus Southwest Airlines at Phoenix, Delta Air Lines versus Morris Air/Southwest Airlines at Salt Lake City, and Delta Air Lines versus Valujet Airlines at Atlanta -- were chosen to provide a wide array of competition levels by which to calculate traditional and low-cost carrier explanatory variable elasticities of demand. It was hoped that not only would elasticities differ between the traditional and low-cost carrier in individual scenarios, but that they would also differ across scenarios depending on the specific competitive characteristics of each scenario. However, it was also expected that general elasticity patterns would emerge across competitive scenarios, so that statements could be made about traditional carrier/low-cost carrier elasticity differentials that were independent of actual local hub market dynamics.

The range of calculated elasticities for the traditional and low-cost airline in each competitive scenario seem to indicate that traditional and low-cost airline passengers do come from distinct passenger markets. For most variables in most competitive scenarios, the ranges of elasticities estimated for the traditional and low-cost airline have little or no overlap. This implies that proportional changes in the explanatory variables have statistically different effects on the numbers of traditional and low-cost airline passengers.

Moreover, a cross-scenario comparison of elasticity range estimates for the traditional and low-cost airlines shows that much of the individual scenario differences are actually independent of the competitive situation. In other words, if the traditional airline's estimated elasticity range for a particular explanatory variable is higher (or lower) than the low-cost airline's elasticity range for that same variable in the same competitive scenario, it is likely that the explanatory variable has a stronger (weaker) effect on the number of traditional airline passengers across all competitive scenarios.

In general, the following cross-scenario differential elasticity effects were observed for the traditional airline relative to the low-cost airline:

1. Changes in the size of socioeconomic variables like population and per capita income were found to have a greater proportional effect on the number of traditional airline passengers.

2. Changes in the size of transport supply variables like airfare, nonstop frequencies and flight time had dissimilar differential effects depending on the type of transport supply variable. Specifically, traditional airline passengers seemed less elastic with respect to airfare and flight time than low-cost airline passengers, but the frequency elasticities seemed to depend more on the relative flight offerings of the two airlines than on individual airline type.

3. The effect of changes in the values of traditional and low-cost airline cross-fare and cross-frequency variables seemed to be mainly a function of the airlines' relative service offerings and the degree to which passengers seemed to substitute one airline for the other. However, the general effect of changes in one airline's fares or frequencies on the other airline's passengers was negligible, except in cases where the traditional airline apparently matched changes in the low-cost airline's fares, when there was a negative effect on traditional airline passengers.

7.2 Directions for Further Research

Although some important and interesting airline passenger demand elasticities were estimated in this thesis, they are only intended as general indicators of the effects of changes in market socioeconomic and airline transport supply variables on traditional and low-cost airline passenger demand in common local hub markets. Several modeling steps are needed before such elasticities could be used for policy purposes or even by traditional or low-cost airlines to determine intelligent pricing, scheduling or market entry strategies against each other.

First, future modeling efforts should be based on greater quantity and quality of passenger demand and explanatory variable data. The elasticities estimated in this thesis are admittedly less precise than those desired because the data is only available by quarter, and because few markets fit the limiting criteria that the traditional and low-cost carrier have a very high combined market share and the market be under 750 miles in distance. One way to improve elasticity estimates would be to collect individual market observations more frequently, like every month, week or even day. Another improvement would be to relax the market share and market distance assumptions, being careful to include new variables that might become critical to proper model specification (for example, if market distance is expanded to include markets in which the low-cost carrier has only one-stop, as opposed to nonstop, service, then a variable for the number of market one-stop frequencies should appear in the demand models.)

Second, the demand models might be expanded to include data for variables which obviously influence the number of traditional and low-cost airline passengers, but which are not believed to be major determinants of airline demand, or are difficult to find or calculate. The best example of such a variable is endpoint dominance -- the effect of frequent-flyer programs, travel agent commission overrides and CRS bias, and other preference intangibles that cause residents of either market originating city to choose one airline over the other. Another example is aircraft size, whose elasticity of demand could serve as a proxy for both amount of passenger spill and passenger preference for certain size aircraft. Finally, the model might include quantitative (not dummy) variables for vacation markets or the proportion of airline market service on non-jet aircraft.

Third, the actual number of airline and market passengers might be replaced by unconstrained booking data to estimate the impact of changes in variable amounts on the potential number of airline and market passengers. Although unconstrained booking data would probably only be available for one airline at a time, the elasticities estimated from demand models with this more accurate indicator of true demand would allow an airline to better plan changes in supply variables like airfare and flight frequency and better predict the amount of demand for its service in new markets. For example, an average fare elasticity calculated from historical actual passenger amounts should underestimate the true average fare elasticity of demand. If an airline were to base, say, a sale fare on the historical elasticity, and its load factors are lower than in the past few years, it may find that it gets fewer bookings than are optimal given the amount of seats it would like to fill.

Fourth, more advanced econometric techniques might be used to better specify traditional and low-cost airline demand models or to estimate separate demand models for each market or for each quarter. For example, one or more variables in a demand model may have no statistically significant effect on passenger demand (perhaps because the values for each airline are about equal and do not vary much). However, by including the variable(s) in the model, elasticity estimates for the statistically significant variables will become less precise. A better specified demand model would take the insignificant variable(s) out of the demand equation.

Last, most airlines make changes in the level of transport supply variables like airfare and flight frequency on a market basis (although the decision to add a new flight is based on the potential amount of and revenue from all local and connecting traffic, there is still an extra flight available to local market passengers) and not across markets as implied by a pooled data set. If data were available on a monthly basis, and it was clear that explanatory variable elasticities did not vary over time, then precise estimation of demand equations for individual markets could be possible. Alternatively, because most airline market demand patterns display seasonality, an airline might want to estimate a large cross-sectional regression to find how individual elasticity estimates vary by month or quarter, and then use this information to plan pricing, scheduling and market entry strategy based on time of year.

Each of the above suggestions would improve estimation of traditional and low-cost airline demand elasticities by allowing model specifications to be better tailored to actual situations than the fixed-model approach used in this thesis. Although it is not likely that the incorporation into airline demand models of some or all of these improvements would be enough for an airline to predict the exact effect of important strategic decisions on itself or its competitor, there is little doubt that model improvement can provide a more precise understanding of how changes in important competitive variables affect an airline's passenger numbers. The growing number of markets in which traditional and low-cost airlines compete should make this information increasingly important to both in future years.

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Appendix A: Source and Derivation of Model Variables

Each demand model observation is a unique quarterly/airline/market combination (for example, Delta Air Lines in Atlanta-New Orleans for second quarter 1994). An observation includes values for each explanatory variable (population, per capita income, average fare, nonstop frequencies, flight time) and the associated number of non-award travel, revenue passengers carried.

The source of the passenger and average fare data is the *O&D+ Origin & Destination Survey of Airline Passenger Traffic* compiled by DataBase Products, Inc. of Dallas, Texas. Note that this data is only a 10% sample of actual passenger and average fare amounts. The source of the population and per capita income data is the *U.S. City and County Local Area Personal Income 1969-1992* published by the U.S. Department of Commerce, Economics and Statistics Administration, Bureau of Economic Analysis. The source of the nonstop flight frequency and flight time data is various issues of the *North American Edition of the Official Airline Guide.*

All demand models were estimated using *Econometric Views* version 2.0 for Windows, created by Quantitative Micro Software of Irvine, California.

The method used to construct each variable follows:

PASSENGERS - Calculated as 10 times the number of passengers appearing in the O&DPLUS+ database for the particular quarterly/airline/market observation.

POPULATION - Because metropolitan area populations were only available by year and only through 1992, population data had to be interpolated and extrapolated on a spreadsheet. First, quarterly population values for the years 1990-1992 were interpolated by simply splitting consecutive yearly numbers in quarters. Then, based on the best fitting exponential growth line, quarterly population numbers were extrapolated for the models' sample period, second quarter 1993 through second quarter 1995.

PER CAPITA INCOME - The per capita income data was extrapolated from actual metropolitan area data in the same way as population.

AVERAGE FARE - Calculated as the average fare of all passengers who paid a fare (and did not use free travel award tickets). Average fare data taken from O&DPLUS+ database.

NONSTOP FREQUENCY - Estimate of the number of quarterly/airline/market nonstop frequencies. First, daily one-way (hub to spoke -- arbitrarily chosen) airline/market nonstop frequencies taken for the last month of the particular quarter by from the O.A.G. This monthly number is assumed to be constant for the quarter. Then, this number is multiplied by 2 (for frequencies both ways) and by 90 (to represent roughly 90 days in a quarter).

FLIGHT TIME - For each airline, the scheduled number of minutes for the first nonstop market flight for the last month of each quarter in the data sample. Total market flight time calculated as simple average of these two numbers.

Appendix B: Individual Phoenix Market Data

City	Statistic	HPPAX	WNPAX	MKTPAX	HP FARE	WN FARE	MKT FARE	POPULA	PERCAP INCOME	HP FREQ	WN FREQ	MKT FREQ	HP FLTTME	WN FLTTME
ABQ	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	25,266	113,118	138,384	$ 56.88	$ 42.45	$ 45.08	646,124	$ 19,675	6	15	21	68	70
	Std. Dev.	1,148	7,392	7,920	$ 3.55	$ 3.46	$ 3.50	8,844	$ 571	0	0	0	0	0
	Maximum	26,724	127,756	153,121	$ 63.90	$ 48.70	$ 51.57	658,212	$ 20,461	6	15	21	68	70
	Minimum	22,984	105,955	130,300	$ 53.70	$ 38.70	$ 41.33	631,716	$ 18,751	6	15	21	68	70
AUS	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	14,212	22,632	36,844	$ 108.90	$ 82.18	$ 92.50	963,502	$ 20,910	3	3	6	131	135
	Std. Dev.	706	1,996	2,243	$ 19.15	$ 7.19	$ 11.21	18,470	$ 666	0	0	0	0	0
	Maximum	15,290	24,924	40,215	$ 155.50	$ 95.20	$ 118.26	988,811	$ 21,828	3	3	6	131	135
	Minimum	13,392	20,298	33,840	$ 97.30	$ 71.70	$ 82.94	933,486	$ 19,834	3	3	6	131	135
BUR	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	36,970	63,816	100,786	$ 54.64	$ 42.34	$ 46.79	9,256,223	$ 22,179	5	6	11	80	75
	Std. Dev.	5,609	6,554	1,575	$ 3.66	$ 2.72	$ 2.52	60,361	$ 239	1	0	1	0	0
	Maximum	45,977	73,461	102,945	$ 62.10	$ 46.90	$ 51.09	9,338,446	$ 22,506	7	7	13	80	75
	Minimum	27,912	54,201	98,238	$ 50.80	$ 39.00	$ 44.17	9,157,576	$ 21,789	4	6	10	80	75
ELP	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	7,772	60,286	68,058	$ 56.88	$ 42.25	$ 43.92	668,941	$ 13,588	4	10	14	70	70
	Std. Dev.	669	4,086	4,112	$ 3.08	$ 2.52	$ 2.57	11,675	$ 375	0	0	0	0	0
	Maximum	9,070	68,612	75,981	$ 62.90	$ 46.30	$ 48.13	684,926	$ 14,103	4	10	14	70	70
	Minimum	7,094	55,278	63,562	$ 52.70	$ 39.50	$ 41.30	649,954	$ 12,981	4	10	14	70	70
LAS	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	51,373	169,244	220,617	$ 54.20	$ 39.46	$ 42.88	1,113,969	$ 21,170	12	19	31	54	55
	Std. Dev.	4,101	9,594	12,719	$ 2.26	$ 1.86	$ 1.85	41,412	$ 387	1	1	1	0	0
	Maximum	56,591	180,729	235,612	$ 57.40	$ 42.20	$ 45.77	1,171,189	$ 21,701	13	20	33	54	55
	Minimum	45,147	156,607	203,286	$ 50.50	$ 37.30	$ 40.59	1,047,215	$ 20,540	10	18	29	54	55
LAX	Observations	5	5	5	5	5	5	5	5	5	5	5	5	5
	Average	78,787	217,353	296,140	$ 53.10	$ 39.58	$ 43.17	9,220,560	$ 22,037	10	25	36	70	65
	Std. Dev.	4,348	16,780	18,064	$ 0.67	$ 1.29	$ 1.33	43,325	$ 171	0	0	0	0	0
	Maximum	86,320	240,391	316,342	$ 53.80	$ 40.80	$ 44.45	9,270,204	$ 22,234	10	26	36	70	65
	Minimum	75,929	197,415	274,592	$ 52.10	$ 37.40	$ 40.93	9,157,576	$ 21,789	10	25	35	70	65
MCI	Observations	3	3	3	3	3	3	3	3	3	3	3	3	3
	Average	25,520	31,783	57,303	$ 122.37	$ 89.73	$ 104.20	1,651,360	$ 23,146	4	5	9	158	160
	Std. Dev.	1,126	4,262	3,801	$ 7.02	$ 7.64	$ 6.00	15,306	$ 1,050	0	1	1	0	0
	Maximum	26,814	36,669	61,652	$ 128.00	$ 97.80	$ 109.95	1,666,690	$ 24,203	4	5	9	158	160

City	Statistic	HPPAX	WNPAX	MKTPAX	HP FARE	WN FARE	MKT FARE	POPULA	PERCAP INCOME	HP FREQ	WN FREQ	MKT FREQ	HP FLTTME	WN FLTTME
	Minimum	24,764	28,831	54,614	$ 114.50	$ 82.60	$ 97.97	1,636,077	$ 22,104	4	4	8	158	160
OAK	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	27,139	56,904	84,043	$ 79.46	$ 55.93	$ 63.48	2,217,379	$ 25,411	5	4	9	112	110
	Std. Dev.	2,245	2,848	3,545	$ 4.91	$ 1.94	$ 2.37	20,269	$ 365	0	0	0	0	0
	Maximum	30,092	61,502	87,906	$ 84.20	$ 59.20	$ 66.53	2,245,023	$ 25,910	5	5	10	112	110
	Minimum	24,373	53,886	78,259	$ 68.20	$ 53.60	$ 59.63	2,184,293	$ 24,816	5	4	9	112	110
ONT	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	36,258	113,722	149,980	$ 54.40	$ 41.94	$ 44.94	3,073,954	$ 17,034	7	16	23	62	60
	Std. Dev.	3,191	8,720	10,376	$ 3.65	$ 2.63	$ 2.83	72,072	$ 37	0	0	0	0	0
	Maximum	39,980	125,913	163,045	$ 62.20	$ 46.20	$ 49.77	3,172,906	$ 17,085	7	16	23	62	60
	Minimum	30,831	98,396	134,575	$ 51.00	$ 39.20	$ 42.28	2,957,055	$ 16,973	7	16	23	62	60
SAN	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	40,627	162,333	202,961	$ 53.05	$ 40.78	$ 43.21	2,708,344	$ 21,095	6	17	23	71	65
	Std. Dev.	3,989	12,756	14,975	$ 3.98	$ 2.81	$ 2.88	31,026	$ 229	0	1	1	0	0
	Maximum	45,922	182,860	228,763	$ 60.90	$ 45.10	$ 47.82	2,750,704	$ 21,408	7	18	25	71	65
	Minimum	32,383	152,560	188,058	$ 47.90	$ 37.70	$ 40.12	2,657,750	$ 20,722	6	15	21	71	65
SMF	Observations	8	8	8	8	8	8	8	8	8	8	8	8	8
	Average	21,279	33,220	54,499	$ 83.05	$ 63.66	$ 71.05	1,503,873	$ 21,530	3	1	5	111	105
	Std. Dev.	1,713	3,252	4,002	$ 15.03	$ 2.67	$ 5.46	23,502	$ 362	0	1	1	0	0
	Maximum	23,720	36,218	59,874	$ 96.60	$ 69.20	$ 77.94	1,536,023	$ 22,025	4	3	7	111	105
	Minimum	19,338	26,564	48,823	$ 62.50	$ 61.10	$ 62.50	1,465,619	$ 20,941	3	1	4	111	105

Appendix C: Individual Salt Lake City Market Data

City	Statistic	DLPAX	KNPAX	MKTPAX	DL FARE	KN FARE	MKT FARE	POPUL	PERCAP INCOME	DL FREQ	KN FREQ	MKT FREQ	DL FLTTME	KN FLTTME
BOI	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	10,249	25,478	35,727	$79.83	$38.33	$50.99	349,017	$21,343	9	3	12	58	55
	Std. Dev.	1,128	11,150	11,713	$13.90	$7.55	$11.22	7,187	$622	1	1	1	0	0
	Maximum	11,619	43,730	54,902	$94.20	$46.10	$68.35	358,185	$22,139	9	4	13	58	55
	Minimum	8,447	10,680	20,362	$64.80	$30.40	$38.81	339,962	$20,561	8	2	10	58	55
COS	Observations	4	4	4	4	4	4	4	4	4	4	4	4	4
	Average	6,100	18,613	24,713	$79.55	$42.60	$53.51	445,822	$20,217	3	2	5	83	80
	Std. Dev.	213	12,582	12,537	$3.00	$1.20	$5.19	4,211	$293	0	0	0	0	0
	Maximum	6,259	36,936	43,016	$82.10	$43.90	$59.68	450,727	$20,559	3	2	5	83	80
	Minimum	5,806	8,312	14,571	$75.30	$41.00	$47.31	440,940	$19,878	3	2	5	83	80
GEG	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	9,016	14,673	23,689	$88.36	$54.00	$68.27	405,361	$20,491	3	1	4	88	90
	Std. Dev.	1,367	9,719	9,851	$10.39	$8.17	$5.16	5,385	$564	0	0	0	0	0
	Maximum	11,612	36,327	45,766	$101.70	$66.40	$76.22	412,878	$21,282	3	2	5	88	90
	Minimum	7,560	8,966	17,810	$72.50	$41.80	$60.43	397,921	$19,717	3	1	4	88	90
LAS	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	20,064	63,102	83,166	$70.70	$40.36	$47.71	1,123,505	$21,260	6	5	11	71	70
	Std. Dev.	2,075	11,076	11,645	$4.04	$4.61	$4.42	33,941	$315	0	2	2	0	0
	Maximum	22,163	75,845	93,594	$75.00	$47.00	$55.31	1,171,189	$21,701	7	8	14	71	70
	Minimum	17,741	40,288	58,502	$63.90	$33.50	$42.41	1,076,920	$20,825	6	3	9	71	70
LAX	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	72,646	73,446	146,092	$85.50	$53.18	$69.21	9,270,315	$22,235	9	4	13	104	100
	Std. Dev.	5,832	14,635	18,541	$3.76	$7.32	$4.45	48,960	$194	0	1	1	0	0
	Maximum	79,215	90,658	169,873	$90.50	$61.80	$74.39	9,338,446	$22,506	9	5	14	104	100
	Minimum	63,793	45,248	112,988	$80.00	$41.40	$62.37	9,202,462	$21,966	9	4	13	104	100
OAK	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	19,611	48,306	67,917	$83.94	$53.16	$61.92	2,222,106	$25,496	4	3	7	94	100
	Std. Dev.	2,335	10,973	10,667	$7.64	$6.58	$5.39	16,455	$297	0	0	0	0	0
	Maximum	21,511	61,026	80,620	$97.40	$61.80	$68.23	2,245,023	$25,910	4	3	7	94	100
	Minimum	14,483	27,673	48,220	$73.10	$42.40	$53.14	2,199,320	$25,085	4	2	6	94	100
PDX	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	31,545	29,823	61,368	$85.50	$54.21	$70.66	1,711,448	$22,612	4	2	6	107	100
	Std. Dev.	2,272	6,967	8,440	$6.26	$7.11	$3.95	23,224	$457	0	0	0	0	0
	Maximum	34,252	42,963	75,998	$93.80	$66.40	$75.27	1,743,868	$23,252	5	2	7	107	100

City	Statistic	DLPAX	KNPAX	MKTPAX	DL FARE	KN FARE	MKT FARE	POPUL	PERCAP INCOME	DL FREQ	KN FREQ	MKT FREQ	DL FLTTME	KN FLTTME
	Minimum	27,984	19,798	47,782	$76.60	$46.90	$63.79	1,679,365	$21,982	4	2	6	107	100
RNO	Observations	4	4	4	4	4	4	4	4	4	4	4	4	4
	Average	8,152	13,788	21,940	$96.50	$41.40	$61.49	287,253	$29,331	5	1	6	76	80
	Std. Dev.	1,240	2,827	2,093	$9.49	$8.81	$9.68	2,155	$471	2	0	2	0	0
	Maximum	9,110	17,264	23,606	$105.50	$52.90	$74.75	289,762	$29,881	7	1	8	76	80
	Minimum	6,342	10,674	19,078	$84.50	$33.20	$52.62	284,754	$28,785	3	1	4	76	80
SAN	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	30,718	34,447	65,166	$77.79	$51.79	$63.71	2,715,572	$21,149	4	2	6	105	105
	Std. Dev.	3,016	6,524	7,275	$6.93	$8.59	$3.29	25,208	$186	0	0	0	0	0
	Maximum	34,901	42,564	72,565	$89.80	$66.40	$67.30	2,750,704	$21,408	4	2	6	105	105
	Minimum	27,524	23,209	53,338	$68.30	$39.80	$57.87	2,680,690	$20,891	4	2	6	105	105
SEA	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	40,560	46,739	87,299	$83.70	$55.94	$69.12	2,880,927	$27,487	4	3	7	108	110
	Std. Dev.	3,483	10,638	13,187	$6.84	$8.40	$3.45	30,654	$802	0	0	0	0	0
	Maximum	46,130	64,915	109,235	$94.10	$72.70	$72.90	2,923,673	$28,614	4	4	8	108	110
	Minimum	36,330	33,268	71,528	$73.20	$47.40	$64.19	2,838,532	$26,386	4	3	7	108	110
SMF	Observations	7	7	7	7	7	7	7	7	7	7	7	7	7
	Average	20,374	17,710	38,085	$84.03	$51.29	$68.31	1,509,338	$21,618	4	1	5	88	90
	Std. Dev.	2,885	3,357	4,086	$6.85	$5.81	$3.00	19,122	$295	0	0	0	0	0
	Maximum	24,467	21,391	43,913	$95.90	$56.80	$70.88	1,536,023	$22,030	4	1	5	88	90
	Minimum	16,637	11,572	31,018	$75.50	$40.60	$63.32	1,482,912	$21,210	4	1	5	88	90
SNA	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	37,320	34,615	71,936	$73.98	$54.33	$64.47	2,565,557	$24,923	3	2	5	98	101
	Std. Dev.	5,173	7,089	11,347	$4.18	$7.66	$3.24	16,528	$86	0	0	0	0	0
	Maximum	43,796	42,503	85,595	$80.50	$61.80	$67.67	2,587,694	$25,037	3	2	5	98	101
	Minimum	31,568	23,876	56,318	$68.30	$41.90	$60.12	2,543,521	$24,808	3	2	5	98	101

Appendix D: Individual Atlanta Market Data

City	Statistic	DLPAX	J7PAX	MKTPAX	DL FARE	J7 FARE	MKT FARE	POPULA	PERCAP INCOME	DL FREQ	J7 FREQ	MKT FREQ	DL FLTTME	J7 FLTTME
BNA	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	32,795	13,835	53,222	$143.97	$53.83	$114.47	1,069,540	$23,796.41	9	4	18	55	55
	Std. Dev.	2,430	4,286	4,742	$29.06	$12.22	$20.40	8,581	$641.88	0	1	1	0	0
	Maximum	37,036	19,587	61,954	$179.90	$60.80	$135.40	1,081,039	$24,662.39	9	4	19	55	55
	Minimum	31,016	8,446	49,135	$103.40	$29.10	$79.00	1,058,106	$22,946.91	9	3	16	55	55
FLL	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	84,544	47,167	136,431	$119.63	$77.93	$103.67	3,451,659	$19,565.76	8	4	13	99	100
	Std. Dev.	17,673	3,818	22,588	$26.00	$2.25	$14.73	25,491	$4.46	1	0	1	0	0
	Maximum	106,853	52,317	165,646	$153.00	$80.00	$121.10	3,485,813	$19,571.72	9	5	14	99	100
	Minimum	65,026	43,578	113,333	$85.30	$73.90	$83.10	3,417,684	$19,559.80	7	4	11	99	100
JAX	Observations	4	4	4	4	4	4	4	4	4	4	4	4	4
	Average	51,633	21,670	76,784	$102.03	$52.28	$86.53	1,001,776	$20,514.48	8	3	12	60	50
	Std. Dev.	6,856	7,021	5,068	$16.09	$9.99	$9.90	6,864	$202.78	0	1	1	0	0
	Maximum	59,743	28,436	83,421	$118.90	$57.80	$94.70	1,009,766	$20,750.69	8	4	13	60	50
	Minimum	43,066	13,861	71,729	$80.80	$37.30	$72.20	993,815	$20,279.47	8	2	11	60	50
MCO	Observations	4	4	4	4	4	4	4	4	4	4	4	4	4
	Average	98,688	40,560	159,018	$105.65	$63.93	$89.58	1,388,827	$19,899.94	9	5	15	79	80
	Std. Dev.	12,804	1,827	12,448	$12.24	$5.64	$7.04	11,501	$202.04	0	1	1	0	0
	Maximum	109,313	42,623	171,448	$119.80	$67.40	$95.20	1,402,218	$20,135.31	9	5	16	79	80
	Minimum	80,061	38,422	143,383	$90.00	$55.50	$80.00	1,375,492	$19,665.81	9	4	13	79	80
MEM	Observations	1	1	1	1	1	1	1	1	1	1	1	1	1
	Average	53,652	24,616	94,183	$86.30	$45.50	$70.70	1,057,847	$21,258.94	8	3	16	63	65
	Std. Dev.	0	0	0	$0.00	$0.00	$0.00	0	$0.00	0	0	0	0	0
	Maximum	53,652	24,616	94,183	$86.30	$45.50	$70.70	1,057,847	$21,258.94	8	3	16	63	65
	Minimum	53,652	24,616	94,183	$86.30	$45.50	$70.70	1,057,847	$21,258.94	8	3	16	63	65
MSY	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	48,251	30,165	82,936	$117.77	$66.53	$96.37	1,326,712	$20,611.79	8	3	12	84	80
	Std. Dev.	6,677	3,983	6,483	$20.21	$3.81	$9.81	4,438	$477.15	0	0	1	0	0
	Maximum	59,014	35,161	94,358	$145.80	$69.20	$108.30	1,332,650	$21,254.67	8	3	14	84	80
	Minimum	38,166	26,469	75,477	$92.90	$59.10	$82.70	1,320,788	$19,979.44	8	3	11	84	80
PBI	Observations	4	4	4	4	4	4	4	4	4	4	4	4	4
	Average	44,796	14,778	61,438	$110.03	$76.00	$100.95	938,635	$33,353.52	9	3	13	93	105
	Std. Dev.	2,765	1,401	618	$7.42	$3.17	$3.69	5,253	$322.02	0	1	1	0	0
	Maximum	47,780	16,419	62,355	$121.00	$79.40	$106.30	944,747	$33,728.60	9	4	14	93	105

City	Statistic	DLPAX	J7PAX	MKTPAX	DL FARE	J7 FARE	MKT FARE	POPULA	PERCAP INCOME	DL FREQ	J7 FREQ	MKT FREQ	DL FLTTME	J7 FLTTME
	Minimum	41,209	13,135	61,004	$105.50	$71.90	$98.40	932,541	$32,980.31	9	2	11	93	105
RSW	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	18,018	10,564	30,094	$123.20	$74.63	$104.28	371,916	$21,466.86	6	2	8	95	105
	Std. Dev.	1,790	1,857	1,841	$20.06	$3.05	$11.16	3,474	$232.13	0	0	1	0	0
	Maximum	20,711	14,158	32,802	$147.20	$78.00	$118.90	376,574	$21,778.26	6	2	11	95	105
	Minimum	15,952	9,035	27,372	$98.00	$70.90	$90.80	367,289	$21,157.86	6	1	7	95	105
SAV	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	18,841	10,113	30,035	$130.52	$51.98	$103.57	278,169	$19,868.46	9	3	11	53	50
	Std. Dev.	2,201	4,302	4,272	$21.36	$10.86	$12.77	2,027	$325.40	0	1	1	0	0
	Maximum	21,376	15,461	33,134	$158.30	$57.70	$125.40	280,884	$20,305.83	9	3	12	53	50
	Minimum	16,025	3,560	22,167	$106.30	$30.00	$88.00	275,467	$19,436.17	8	2	10	53	50
SDF	Observations	6	6	6	6	6	6	6	6	6	6	6	6	6
	Average	23,851	23,725	51,422	$123.47	$53.62	$90.40	990,588	$23,097.38	7	4	11	70	70
	Std. Dev.	3,824	3,969	5,453	$23.57	$4.56	$9.28	4,155	$568.03	0	1	1	0	0
	Maximum	29,677	27,840	61,248	$149.80	$56.80	$102.10	996,148	$23,863.08	7	4	11	70	70
	Minimum	19,842	16,761	46,911	$88.60	$44.50	$75.00	985,044	$22,344.98	6	3	9	70	70
TPA	Observations	4	4	4	4	4	4	4	4	4	4	4	4	4
	Average	95,720	36,572	150,711	$102.95	$65.43	$89.98	2,147,095	$21,131.52	9	4	15	81	85
	Std. Dev.	13,024	2,101	16,546	$14.39	$6.10	$9.09	5,200	$262.86	0	0	2	0	0
	Maximum	111,350	39,379	173,507	$117.10	$69.40	$96.80	2,153,141	$21,437.91	9	4	17	81	85
	Minimum	79,510	34,664	134,284	$83.50	$56.40	$76.60	2,141,057	$20,827.09	9	4	13	81	85